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Financial News Sentiment Analysis Using NLP and Machine Learning for Asset Price Prediction: A Systematic Review

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Abstract

Forecasting market movements in stocks, gold, and crude oil requires a deep understanding of how financial news sentiment influences asset prices. Analyzing news sentiment is crucial for understanding market dynamics and forecasting price fluctuations. However, creating accurate financial news datasets, particularly in terms of proper labeling and sourcing, continues to be a significant challenge. This paper presents a comprehensive literature review on financial news sentiment analysis and its application in market trend prediction.By reviewing articles in reputable journals from 2018–2025, we consolidate key findings, including techniques for dataset creation, labeling, and sourcing, as well as the use of advanced methods such as Natural Language Processing (NLP) and deep learning models. This review contributes to the growing literature on sentiment analysis in the context of the relationship between stocks and commodities, especially gold, crude oil, and the role of global and market specific news sentiments in determining the assets prices. The study focuses on issues that concern researchers in this regard; it also compares the relative success of various prediction models and discusses the criteria for assessing their effectiveness.We propose solutions to current challenges and outline future research directions to improve sentiment analysis in financial markets.

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1 Introduction

Financial markets are affected by various factors, one of which includes sentiment about financial news-a measure of tone and implications attached to the news content.News sentiment influences investor behavior and market trends and adds a predictive signal to price models. Studies indicate that sentiment metrics derived from financial news headlines significantly improve the precision of price predictions for stocks and commodities such as crude oil and gold [1]. Advanced machine-learning models support this improvement. CNN–LSTM models process sentiment sequences effectively and improve price-movement forecasts [14].

Global and regional sentiment jointly shape equity and commodity markets. Market sentiment is therefore influenced by key global events, including changes in US monetary policy and changes in geopolitics, among others. These changes affect investor confidence and create volatility in the market [2]. Domain-specific NLP models e.g., FinBERT captures rapid news-driven moves [90]. Furthermore, trading strategies that incorporate sentiment analysis have been shown to outperform traditional approaches in various market conditions, particularly when integrating both global trends and industry-specific developments. These insights suggest that sentiment analysis is an essential tool for financial prediction in an increasingly interconnected and complex world [50]. Integrating qualitative news with quantitative financial data highlights the significance of sentiment analysis in financial markets. This paper shows that sentiment analysis improves the ability to understand differences between related activities and the fundamental causes of market trends. For example, studies using causal inference techniques have shown that sentiment metrics can filter out background noise to isolate genuine market-moving news, thus improving financial modeling by capturing the interconnectedness of global markets [2, 50].

Despite the increasing use of sentiment analysis in financial markets, there is no unified synthesis of techniques applied across multiple asset classes such as stocks, crude oil, and gold. Existing studies focus on isolated aspects, either evaluating the impact of sentiment on a single asset class or applying limited methodologies that fail to capture the inter dependencies between global and market-specific news. Furthermore, while deep learning models such as CNN-LSTM and BERT have shown promise in sentiment classification, their comparative effectiveness in financial forecasting remains underexplored.

Many studies blur correlation and causation, obscuring whether sentiment drives market moves. Most notably, existing systematic literature reviews tend to examine stocks or commodities independently, without exploring their interconnections. No comprehensive study has analyzed how market sentiment influences asset price fluctuations in both asset classes. This review offers a unified framework spanning equities and key commodities to analyze sentiment-driven dynamics. We synthesize findings, compare modeling techniques, and assess causal designs to separate co-movement from market-moving news.

Specifically, this paper aims to review and discuss the ways and means of applying financial news sentiment analysis policies to anticipate stock and commodity prices while identifying the methodologies and causalities of the field, as well as evaluation criteria commonly used by experts.

The structure of the paper is as follows. Section 2 outlines the research methodology, detailing the research questions, the inclusion and exclusion criteria for the studies, and the methods used to gather and analyze the relevant literature. This section provides a very strong background and a well-justified process on how the systematic literature review will be established.Section 3 addresses the research questions, discussing the techniques for constructing and annotating sentiment datasets,the methods used to forecast trends in prices, and the relationships between important financial assets, including stocks, gold, and crude oil. It also looks at the general trends in global and market-specific sentiments and conducts an integrity evaluation of causality in the advancement of prediction methods. Section 4 introduces the taxonomy of the literature review, while Section 5 outlines the key findings and discusses the results in detail. Section 6 outlines the major challenges and unresolved issues in the field of financial news sentiment analysis to predict price movements. Section 7 offers recommendations for future research directions. The last on the list is Section 8 that gives a brief conclusion of the study and makes a proposal on the future of sentiment analysis for financial forecasting offering both the opportunities and risks of the practice. This structured approach ensures a comprehensive exploration of the topic, offering valuable insight into the role of sentiment analysis in financial markets [70].

1.1 Background

Over the years, Sentiment analysis quantifies textual information and its impact on prices. Numerous studies show how news sentiment influences price movements in stocks, commodities, and energy markets. Evidence is heterogeneous across regimes (policy cycles, crises, pandemics), and effectiveness can be regime-dependent. A cross-asset, cross-regime synthesis remains scarce. This gap justifies the need for a systematic review.

Existing research has laid a solid foundation for understanding the role of sentiment analysis in financial markets. For instance, Patil et al. in [106] applied sentiment analysis tools such as NLTK Vader with machine learning models such as Random Forest and LSTM to predict stock market movement and showed that adding sentiment triples predictive accuracy.

Usmani and Shamsi [82] show that weighting news by market category relevance (WCN-LSTM) improves stock prediction on the Pakistan Stock Exchange.

Omura and Todorova [77] applied quantile regression to examine the asymmetric effects of sentiment on energy commodities, industrial metals, and gold. Their findings suggest that negative sentiment had a stronger impact on returns during financial crises, likely due to increased market uncertainty and risk aversion. Sahut et al. suggested that sentiment-based indexes provide superior crude oil price forecasting performance compared to conventional methods in times of high volatility (e.g. epidemic pandemics of COVID) [71]. Furthermore, Liu et al. in [49] have shown that merging sentiment attention mechanisms with deep learning models such as TrellisNet would enhance the forecast ability on the global stock index by incorporating sentiment and historical stock data.

Collectively, these studies indicate sentiment's incremental predictive value for prices and market behavior. Despite these advances, the lack of a unified synthesis across diverse asset classes and market conditions limits the broader applicability of sentiment analysis. By substantiating this consolidation of existing research with a comprehensive perspective, this review hopes to bridge the gaps and prepare the ground for more robust applications of sentiment analysis in financial forecasting and decision making.

1.2 Motivation

Financial markets are deeply interconnected and highly sensitive to news and sentiment, making sentiment analysis a valuable tool for predicting price movements. Nevertheless, as the field has gained more attention and progress has been made, the problem remains dispersed. Most of the research is confined to one market such as stock,crude oil or gold- without considering how sentiment-driven movements in one market influence others. This interdependence is critical because financial assets do not operate in isolation; price fluctuations in commodities can impact stock markets and vice versa. However, no comprehensive study has been conducted that compares different asset classes in a unified framework, limiting our understanding of cross-market sentiment spillover effects.

Furthermore, while global sentiment analysis has been thoroughly researched, the effect of market-specific local news sentiment on price movement has not received much attention, especially in periods of high volatility. Moreover, existing techniques do not handle the challenging task of capturing the nuanced language of financial news, which limits the ability of financial news analysis itself to distinguish between correlation and true causal relationships between price fluctuations. Furthermore, the lack of universal evaluation metrics impedes further improvement in the reliability of predictive models across different financial markets.

The second and a major obstacle is the fact that there are not many publicly available datasets that support sentiment analysis and predict prices. Building and annotating datasets that reflect sentiment and asset price relationships is a difficult job that researchers often struggle to do. Because each asset class is sensitive to different sentiment driven events and requires different analytical methods, such a comparative analysis has never been conducted systematically.

In this review, research gaps are bridged by providing an integrated context that covers the sentiment analysis of multiple financial assets, the conditions under which sentiment is introduced into price movements across interconnected markets, and the most suitable ways for distinct financial assets. This study seeks to fill critical research gaps, highlight important trends, and offer insights that will aid in the creation of more accurate predictive models for the benefit of researchers, investors, and policymakers.

1.3 Contribution

This systematic literature review provides substantial implications to the field of financial news sentiment analysis and its impact on market prices. By doing so, it combines evidence from stock markets, oil, and gold markets and captures the inter linkages and spillovers that single asset studies often overlook.

This review presents a novel perspective on how global and local news sentiments affect market activity, especially in periods of turbulent or geopolitical shifts. It compares the most efficient techniques used in sentiment analysis, including machine learning, deep learning, and lexicon-based approaches. In addition, it evaluates methodologies to distinguish causation from mere correlation, providing a deeper understanding of market sentiment effects. Moreover, this review also identifies the key challenges in the current research, including a scarcity of datasets and a lack of agreement on evaluation metrics, and presents potential solutions to address these problems, offering a path toward more robust sentiment analysis in financial markets. In particular, this paper provides valuable recommendations for investors, policymakers, and market analysts in the areas of risk and sentiment-based decision making and management.

2 Research Methodology

This systematic literature review (SLR) follows the IEEE SLR framework to ensure a structured and systematic approach to analyzing existing research. The process begins by establishing clear research objectives that define the focus of the study and guide the overall direction. From these objectives, well-defined research questions are formulated to address key gaps in the literature. To find the most relevant studies, a search strategy is carefully designed using a well constructed search string that includes carefully chosen keywords and Boolean operators. This ensures that the search retrieves high-quality research aligned with the scope of the study. To further refine the selection, inclusion and exclusion criteria are applied, filtering studies based on relevance, methodological rigor, and publication quality. The selection process involves multiple stages, including title and abstract screening, full-text review, and final selection, so that only the most relevant articles are included. To maintain credibility, a quality assessment is conducted, evaluating each study against predefined criteria to ensure reliability and robustness. Finally, key findings are extracted in the data extraction and synthesis stage, where insights are categorized and analyzed systematically. This structured yet flexible approach ensures a comprehensive review of existing knowledge while maintaining transparency and reproducibility in the research process.

2.1 Research Objectives

This research was based on the following objectives:

- Identify the sources, formation techniques, and labeling techniques used in the creation of financial news datasets for sentiment analysis.
- Analyze the sentiment analysis techniques used to predict the stock or commodity price movement from financial news.
- Examine the role of global and market-specific news sentiment in influencing price volatility in stock and commodity markets.
- Investigate the spillover effects and inter dependencies between different asset classes (stocks, gold, and crude oil).
- Understand the challenges and restrictions of sentiment analysis techniques in relation to financial news and their practical utilization for speculation examination.
- Analyze the use of causal inference techniques to differentiate between correlations and causal relationships in the impact of news sentiment on market prices.
- Propose future research directions for improving sentiment analysis methodologies and integrating them into financial decision making systems.

2.2 Research Questions

The initial phase of a systematic literature review involves formulating structured and effective research questions, as they are critical to the research process. These questions help identify the gaps in the existing body of knowledge highlighted by previous studies. This systematic literature review includes seven research questions, as presented in table 1. Table 1 outlines each research question along with its corresponding motivation.

2.3 Search Strategy

For this systematic literature review (SLR), we developed a structured search strategy to identify high-quality research on sentiment analysis in financial markets, focusing on articles published between 2018 and 2025. The process began with defining our research questions, followed by a comprehensive search strategy to identify the most relevant studies. Keyword selection played a crucial role in ensuring comprehensive coverage of relevant studies across multiple databases.

We explored publicly recognized academic databases such as ScienceDirect, SpringerLink, IEEE Xplore, and Web of Science to guarantee comprehensive discussion of relevant papers. In ScienceDirect, for instance, we used keywords like "financial news OR sentiment analysis" combined with "stock price prediction OR commodity price prediction OR gold price." This search resulted in roughly 5,000 results. After carefully going through them, we honed in on 53 papers that were highly relevant. IEEE Xplore, with the same keyword strategy, returned about 2,500 articles. After screening these, we ended up with 27 selected papers. Similarly, SpringerLink gave us 900 results and, after review, we finalized 09 articles for inclusion. Web of Science, with the same query, produced around 2,000 results, of which 15 papers were finally selected. In addition, we directly searched some titles not captured through keyword queries, which yielded 05 more relevant papers. The overall results are summarized in Table 2.

Sources	Extracted Papers	Final Papers Selected
ScienceDirect	5, 915	53
IEEE Xplore	2500	27
SpringerLink	250	09
Web of Science	2,000	15
Direct Search	40	05

Table 2. Number of Extracted and Final Papers from Databases and Manual Search.

Figure 1 illustrates the distribution of the final papers selected from each database after applying the inclusion and exclusion criteria. This graph provides a clear representation of the number of relevant studies chosen from databases such as Web of Science, ScienceDirect,IEEE Xplore, Springerlink and through manual search highlighting the contribution of each source to the review.

To keep the review focused and high-quality, we applied strict criteria. Only peer-reviewed papers addressing sentiment analysis in financial markets published in the selected timeframe were included. We excluded papers that were irrelevant, non-peer reviewed, duplicate, or out of scope. This meticulous process ensured that we worked with a solid collection of studies, providing a strong foundation for exploring our research questions and drawing meaningful insights.

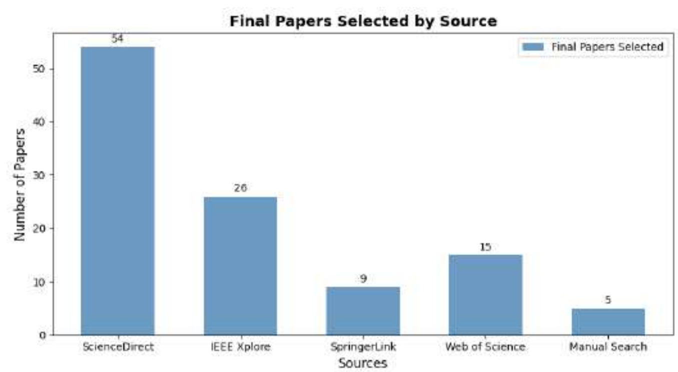

Figure 1. Bar graph of final papers selected from Database

2.3.1 Search String

Several search strings were created that involved financial news, sentiment analysis, price prediction across asset such as stocks and commodities. These strings were created in order to obtain key points in the research questions and to obtain a comprehensive retrieval of relevant papers. Table 3 provides a detailed grouping of search strings.

2.4 Inclusion and Exclusion Criteria

To ensure the quality and relevance of the studies included in this systematic literature review, clear inclusion and exclusion criteria were established. The choice of this criteria was carefully made to discard all irrelevant or low quality research while focusing

Sr.No	Group	Search String
1	Group 1	Financial News OR Sentiment Analysis AND Price Prediction
2	Group 2	Financial news classification AND price prediction
3	Group 3	sentiment analysis AND price prediction
4	Group 4	Financial news OR sentiment analysis AND gold price prediction
5	Group 5	Financial news OR sentiment analysis AND crude oil price
6	Group 6	financial news OR sentiment analysis AND (stock price prediction OR commodity price prediction

Table 3. Search Strings used to identify relevant studies

only on research that is directly related to the area of sentiment analysis in financial markets. The criteria are summarized in table 4.

Inclusion Criteria	Exclusion Criteria
Studies which were included published in peer-reviewd journals or high quality conference proceedings	Non-peer-reviewed articles, blog posts, or non-academic sources.
Research focusing on sentiment analysis and price prediction techniques in financial markets (stocks, commodities specially gold and crude oil)	Studies that are unrelated to financial sentiment analysis or focus on forex prices or commodities other than gold and oil.
Studies addressing the casual interference and inter-dependencies between stocks ,gold and crude oil	Papers focusing purely on theoretical aspects without empirical evidence.
Studies published between 2018-2025	Duplicate studies were removed

Table 4. The inclusion and exclusion criteria for the systematic literature review

2.5 Selection Process and Results

As mentioned earlier, the downloaded articles went through an initial screening process, based on inclusion criteria. A total of 10,655 records were gathered from Springe, IEEE Xplore, and ScienceDirect for this systematic review. After removing duplicates and going through an initial title screening process, 10,355 records were excluded. Of the remaining 300 articles assessed by their abstracts and conclusions, 191 were found irrelevant to the research questions or objectives. Ultimately, 109 studies were finalized for inclusion, ensuring a focus on high-quality and relevant literature. This process, summarized in the PRISMA diagram in Figure 2, highlights the systematic approach used to refine and select studies for review.

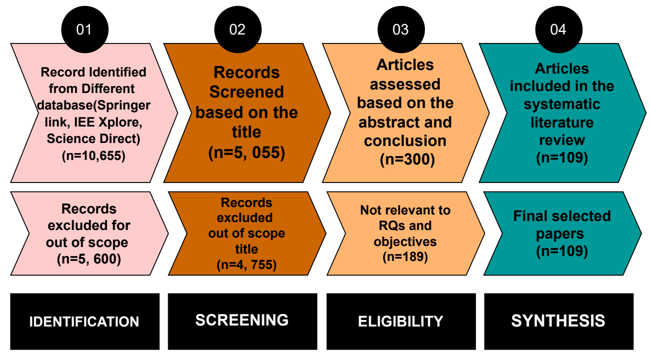

Figure 2. PRISMA diagram illustrating the systematic process of study selection.

2.6 Quality Assessment

Table 11 provides a quality assessment of the selected articles,including the type of publication. It shows that of the 109 papers, 80 were published in journals, while the remaining 29 appeared in conference proceedings. The publications span from 2018 to 2025 and detail the nature of the research, whether it is empirical, along with the research methodology used. Most of these papers are classified into applied and experimental research categories using time series and computational methods. The table 11 also features specific columns: (a) indicates if a framework/ model is used in the study, (b) assesses if the methodology is clearly outlined, (c) examines if the results are thoroughly described, and (d) evaluates the ranking of the journal or conference based on the SJR (SCImago Journal Rank).

The scores in the table 11 represent the quality and reliability of studies based on the criteria discussed above. Higher scores (7–8) indicate highly credible studies published in top-tier journals or conferences, while lower scores (<=6) reflect limitations in these aspects. This evaluation ensures the selection of impactful and reliable research for the review.

2.7 Data Extraction and Synthesis

We systematically extracted and synthesized data from 109 studies included in this review. Through a predefined framework that could extract relevant data, key information such as study objectives,

Ref	Classification					Quality Assessment				
	P. Channel	Publication Year	Research Type	Empirical Type	Methodology	(a)	(b)	(c)	(d)	Score
[1]	Journal	2018	Applied	Quantitative	Time Series Analysis	1	1	2	4	8
[2]	Journal	2019	Fundamental	Quantitative	Time Series Analysis	1	1	1	4	7
[3]	Journal	2019	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[4]	Journal	2025	Fundamental	Qualitative	Time Series Analysis	1	1	1	4	7
[5]	Journal	2022	Empirical	Quantitative	Time Series Analysis	1	1	2	4	8
[6]	Journal	2021	Applied	Qualitative	Time Series Analysis	1	1	1	4	7
[7]	Journal	2024	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[8]	Journal	2022	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[9]	Journal	2022	Applied	Quantitative	Time Series Analysis	1	1	2	4	8
[108]	Journal	2024	Empirical	Quantitative	Computational	1	1	2	4	8
[10]	Journal	2024	Fundamental	Qualitative	Time Series Analysis	1	1	2	4	7
[11]	Journal	2024	Applied	Quantitative	Computational	1	1	2	4	8
[12]	Journal	2023	Applied	Qualitative	Time Series Analysis	1	1	1	4	8
[13]	Journal	2024	Empirical	Quantitative	Computational	1	1	2	3	7
[14]	Journal	2019	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[15]	Journal	2024	Applied	Quantitative	Machine learning	1	1	2	4	8
[16]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[17]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[18]	Journal	2023	Applied	Quantitative	Time Series Analysis	1	1	2	4	8
[19]	Journal	2022	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[20]	Journal	2021	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[21]	Journal	2023	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[22]	Journal	2024	Empirical	Qualitative	Machine learning	1	1	2	4	8
[23]	Journal	2022	Fundamental	Qualitative	Time Series Analysis	1	1	2	4	8
[24]	Journal	2024	Applied	Quantitative	Time Series Analysis	1	1	2	4	8
[25]	Journal	2023	Applied	Quantitative	Time Series Analysis	1	1	2	4	8
[26]	Journal	2024	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[27]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[28]	Journal	2023	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[29]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[30]	Journal	2023	Empirical	Quantitative	Time Series Analysis	1	1	2	4	8
[31]	Journal	2024	Applied	Quantitative	Computational	1	1	2	4	8
[32]	Journal	2023	Fundamental	Qualitative	Time Series Analysis	1	1	2	4	8
[33]	Journal	2024	Fundamental	Qualitative	Time Series Analysis	1	1	2	4	8
[34]	Journal	2021	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[35]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[36]	Journal	2023	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[37]	Journal	2022	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[38]	Journal	2023	Fundamental	Qualitative	Time Series Analysis	1	1	1	4	7
[39]	Journal	2023	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[40]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[41]	Journal	2024	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[42]	Journal	2024	Fundamental	Quantitative	Time Series Analysis	1	1	2	3	7
[43]	Journal	2021	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	7
[44]	Journal	2021	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[45]	Journal	2023	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[46]	Journal	2022	Fundamental	Quantitative	Time Series Analysis	1	1	2	4	8
[47]	Journal	2023	Applied	Qualitative	Time Series Analysis	1	1	2	4	8
[48]	Journal	2024	Empirical	Quantitative	Time Series Analysis	1	1	2	4	8
[49]	Journal	2022	Empirical	Quantitative	Time Series Analysis	1	1	2	4	8
[50]	Conference	2020	Empirical	Quantitative	Text Mining	1	1	2	4	8
[51]	Conference	2025	Applied	Quantitative	Time Series Analysis	1	1	2	4	8
[52]	Conference	2025	Applied	Quantitative	Time Series Analysis	1	1	1	4	7
[53]	Conference	2023	Applied	Qualitative	Computational	1	1	2	4	8
[54]	Conference	2023	Empirical	Quantitative	Text mining	1	1	2	4	8
[55]	Conference	2023	Applied	Quantitative	Machine learning	1	1	1	4	7
[56]	Conference	2022	Empirical	Quantitative	Time Series Analysis	1	1	2	4	8
[57]	Conference	2020	Applied	Quantitative	Computational	1	1	2	4	8
[58]	Conference	2023	Empirical	Quantitative	Text mining	1	1	2	4	8

methodologies, data sources, analyzed variables, sentiment analysis techniques, evaluation metrics, and results were extracted. We documented metadata such as publication year, author details, and journal sources.We meticulously recorded study characteristics in scope, target markets (stocks, oil, gold), and focus on certain financial instruments. Furthermore, we extracted methodological details (use of sentiment analysis techniques like machine learning (ML) models, e.g. CNNs, LSTMs, and natural language processing (NLP) methods, datasets, and tools to thoroughly explain our research questions in Section 3. We categorized studies by markets and sentiment analysis techniques to synthesize data for comparative analysis of methodologies to find the best options for price prediction. Thematic trends were rooted in key qualitative insights, such as filter bubbles, sentiment towards global and market-specific news affecting financial instruments, sentiment behind decisions of institutional investors, and others. We also collected qualitative accounts alongside quantitative data (evaluation metric scores), which were tabulated to enable cross-study comparisons. A structured approach provided insight into the efficacy of various methodologies and highlighted gaps in the current literature, creating a resilient base from which to work with the research questions.

3 Literature Review

This section addresses the main questions behind this review, as outlined in Table 1, all centered on how news sentiment impacts financial markets. This review focuses on previous research on stocks, crude oil, and gold, analyzing how sentiment analysis is used to predict price changes and understand market behavior. By delving into methodologies, causal relationships, evaluation metrics, and the role of global and market-specific news, this review highlights the connection between sentiment and price volatility. Furthermore, this section talks about the challenges, research gaps, and connections among the markets, laying the groundwork for deeper research in this space.

RQ1:What are the publication sources and their corresponding geographical locations for the studies?

The table 6 shows that IEEE Xplore is the leading journal with 26 publications, making it a key player in research on sentiment analysis and financial forecasting. Of the 49 journals listed in the table 6, a few others also stand out. For example, Resources Policy has 12 papers that focus on finance and commodities, while Energy Economics contributes 9, highlighting its role in energy markets and sentiment studies and ,the International Review of Financial Analysis with 5 publications emphasizing its influence in financial forecasting. Interdisciplinary journals like PLOS ONE and Expert Systems with Applications each have 3 papers, showing how advanced systems play a role in financial predictions. This spread of contributions reflects the variety and importance of journals shaping this field and serves as a solid guide to impactful sources.

Sr.No	Publication Source	No.of Publications
40	Journal of Management Mathematics	1
41	European Journal of Political Economy	1
42	Technological Forecasting and Social Change	1
43	Journal of International Financial Markets, Institutions and Money	1
44	Expert Systems With Applications	1
45	springer Annals of Operations Research	1
46	Decision Support Systems	1
47	Computational Management Science	1
48	Information Fusion	1

Table 6. Distribution of Publications Across Sources and Their Respective Publication Counts

Table 7 shows the geographical distribution of publications, revealing global interest in the area of sentiment analysis and financial market research, with a long reach to multiple continents.

The leading contributor was Asia, made up of India and China, who had 24 and 22 publications,respectively . In Asia, several other countries, including Pakistan, Saudi Arabia, Turkey, Thailand, Hong Kong, South Korea, Indonesia, Japan and Taiwan, have also made notable contributions with

Sr.No	Publication Source	No.of Publications
1	Ieee	27
2	Resources Policy	12
3	Energy Economics	9
4	International Review of Financial Analysis	5
5	plos one	3
6	Expert Systems With Applications	3
7	Heliyon	3
8	Decision Analytics Journal	2
9	North American Journal of Economics and Finance	2
10	knowledge Based systems	2
11	peer j computer science	2
12	Association for Computational Linguistics	1
13	SCITEPRESS	1
14	Journal of LATEX Templates	1
16	ESP International Journal of Advancements in Computational Technology	1
17	applied economics	1
18	CESifo Group Munich	1
19	International Journal of Data Science and Analytics	1
20	arXiv	1
21	algorithms	1
22	Computational Economics	1
23	Computational Social Science	1
24	Connection Science	1
25	Spatial Information	1
26	International Journal of Finance and Economics	1
27	Journal of Computing and Biomedical Informatics	1
28	Modern Finance	1
29	studies in economics and finance	1
30	journal of futures markets	1
31	Hawaii International Conference on System Sciences	1
32	Global Finance Journal	1
33	Seventh Information Systems International Conference (ISICO 2023)	1
34	Journal of Commodity Markets	1
35	Economic Analysis and Policy	1
36	Extractive Industries and Society	1
37	Finance Research Letters	1
38	International Review of Economics and Finance	1
39	Applied Energy	1

multiple publications. European contributions were led by Germany with five publications, followed by the UK, Italy, France, and Ireland with multiple contributions. Additional publications were from countries such as the Czech Republic, Norway, Poland, Switzerland, and Greece. Oceania was represented by Australia and New Zealand, while South America and Africa contributed through countries such as Brazil, Colombia, and Tunisia. This broad distribution highlights the global and diverse nature of research in this domain, with Asia emerging as the leading region in terms of publication output.

Subcontinent	Country	No. of Publications
Asia	India	25
Asia	China	20
North America	United States	09
Oceania	Australia	05
Europe	Germany	04
Asia	Pakistan	04
Asia	Saudia Arabia	03
Asia	Turkey	03
Europe	UK	03
Europe	Italy	03

Subcontinent	Country	No. of Publications
Europe	France	03
Asia	Thailand	02
Asia	Hongkong	02
Europe	Ireland	02
Asia	South Korea	02
Asia	Indonesia	01
Oceania	New Zealand	02
North America	Canada	02
Asia	Taiwan	02
Europe	Czech republic	01
Europe	Norway	01
Asia	Jordan	01
Europe	Poland	01
Asia	Japan	02
Africa	Tunisia	01
Asia	Oman	01
South America	Colombia	01
Asia	Iran	01
South America	Brazil	01
Europe	Switzerland	01
Europe	Greece	01

Table 7. Geographical distribution of publications on sentiment analysis and financial market research across continents.

The figure 3 represents the geographical distribution of the publications, showcasing contributions from various countries and regions. It highlights the prominence of research in Asia, followed by notable contributions from Europe, Oceania, North America, South America, and Africa. The figure effectively visualizes the diverse and global nature of research efforts in the field.

RQ2: What are effective techniques for preprocessing and annotating a financial news dataset for sentiment analysis to predict future prices?

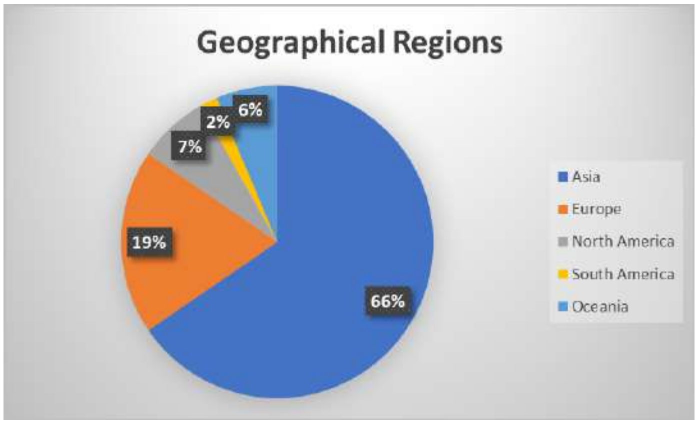

Figure 3. Percentage of the contributed subcontinents

In our world, the market for stocks, oil, gold, and gas and all kinds of assets can be estimated with the help of the sentiment analysis tool. Sentiment analysis is about studying the emotional tone in news articles and other textual sources to see how the emotional tone may impact markets currently due to investor feelings. For instance, in the stock market, the sentiment of news reports is often correlated with stock price fluctuations, and investors react to the most recent company updates or economic information [98].

In the oil market, sentiment derived from news stories has been shown to improve forecasting accuracy, with traditional media offering more insightful information than social media [18].

Similarly as in the gold market, being able to understand sentiment helps you predict price changes in such a market, which is a combination of financial news and macroeconomic factors [5].

As the amount of data involved becomes so vast, the need for reliable data processing and accurate annotation is absolutely essential. Large volumes of news content are processed with techniques such as term frequency-inverse document frequency (TF-IDF) and natural language processing (NLP) to sift through the noise to extract meaning [107]. Using these methods to classify and process the sentiment of news, analysts can make better predictions about price movements, making sentiment analysis a powerful tool to navigate today's financial markets [1, 18].

3.0.1 Common Sources of Financial news Dataset

Data collection is the critical first step in creating a financial news dataset to use in market prediction models. One of the scraping news articles from different kinds of sources i.e. financial news websites, social media platforms, and press releases. Table8 shows some of the common sources from which financial news can be scrapped. The table 9 presents the specific sources of historical price data for gold, stocks and crude oil.

The process of predicting stock prices or commodity movements based on the sentiment of financial news involves several key steps: data preprocessing, data extraction, and data annotation. These steps are crucial for transforming raw data into a structured format suitable for machine learning models.

1. **Data Preprocessing**
   Preprocessing typically begins with cleaning the text to remove unnecessary symbols, numbers, punctuation, and stopwords, followed by tokenization to break the text into words or phrases for sentiment analysis. Normalization is then applied, usually by converting text to lowercase, and lemmatization is used to reduce words to their base forms to treat variations of words like "running" and "ran" as the same. Stopwords that do not provide significant sentiment value are removed to reduce noise in the data, and missing data is handled by interpolation or data imputation to ensure that the analysis is not affected by gaps in the dataset [106]. Sentiment scores are often normalized to maintain consistency across the dataset, making the model less sensitive to scale variations [50].
2. **Data Extraction**
   Data extraction begins with gathering the necessary information from external sources, such as financial news platforms, social media, and stock market data. To gather real-time and historical news articles from sites like Bloomberg, Reuters, Yahoo Finance to capture high-frequency sentiment data that reflect immediate market responses, web scraping is a popular method used to crawl such sites to find objects of interest

Source	Overview	References
Yahoo Finance	These platforms provide tremendous historical data on stock prices (OHLC), trading volumes, financial metrics. For stock market analysis, price data is combined with sentiment from news, enabling them to predict price movements and test model accuracy, and are invaluable.	[80][54] [86][103] [89] [14] [72][94] [60] [64] [76]
Bloomberg	Bloomberg offers both real-time and historical data, providing a comprehensive set of stock, commodity, and index prices. This platform is essential for financial market analysis, it includes historical data crucial for developing predictive models.	[70][109][16][93][79] [22][104]
Social Media (Twitter, Reddit)	Real time sentiment data from social media platforms such as Twitter and Reddit can be aligned with historical market data to make short term market predictions. In volatile markets where sentiment can change very quickly, these platforms become especially valuable.	[95][73][42][54][58] [62] [2] [18]
Thomos Reuters and News Analytics	Global macro information, combined with sentiment analysis, is available through platforms such as RavenPack News Analytics and Thomson Reuters NewsScope. The combined data is crucial in understanding the effect of global events, including recessions, or pandemics, on (commodity) products, like oil or gold.	[96][77][75][16][24]
Financial times	financial archives such as those contained in Reuters and the Financial Times are used to capture long term trends and to better understand the economic context that influences asset prices over long periods.	[100][43][1]

Table 8. Overview of Sources for Financial News Datasets

Source	Overview	References
Coin market cap	Known for tracking cryptocurrency data, CoinMarketCap provides historical price data for assets like Bitcoin, Ethereum, and other cryptocurrencies. This data is particularly useful for studying the influence of sentiment extracted from financial news on cryptocurrency prices.	[73]
SET100 Index and BSE	These sources provide historical stock price data for the Indian market, particularly for predicting market movements based on sentiment analysis combined with local stock data	[68]
COMEX (Gold Futures)	As the primary exchange for gold futures contracts, COMEX provides comprehensive historical gold price data, including OHLC values. This data is vital for analyzing gold price fluctuations and understanding the impact of macroeconomic events and geopolitical tensions.	[73] [6] [7]
WTI Crude Oil Index	The WTI crude oil index offers historical data on crude oil prices. This data is crucial for understanding how geopolitical events and economic shifts impact oil prices. It is often integrated with news sentiment data to predict oil price movements.	[75][1] [11] [23] [22]

Table 9. Overview of Sources for Historical price data

[96]. Next, we apply text mining techniques to generate features such as noun phrases, named entities, or more specific event mentions that can influence stock prices [70]. The polarity of news articles is analyzed using tools such as VADER, SentiWordNet, or Harvard IV (HIV4) and cuts of these with polarity scores are aggregated across the news articles. Furthermore, by computing the transfer entropy, we explore the causal relationship between the target firm and the related firms and assess the amount of news that affects stock movements [95].

3. **Data Annotation**

Data annotation is essential for training supervised machine learning models, as it involves labeling the data with relevant information such as sentiment labels or price movements [70]. Some studies use manual annotation to tag news articles with sentiments such as positive, negative, or neutral, especially for smaller datasets where high precision is required. For larger datasets, automated techniques such as Support Vector Machines (SVM) and Neural Networks are employed to classify news articles based on sentiment, with models trained on previously annotated data to learn the relationship between sentiment and stock market movements [56]. Supervised learning models such as Random Forests, LSTM, and ARIMA are often used to predict stock movements based on sentiment scores extracted from the news [93]. Some studies categorize news into different types, such as news related to the market, sector, or individual stocks, and assign weights to these categories to enhance prediction models by analyzing how different types of news impact the stock market [50].

In conclusion, data preprocessing, extraction, and annotation techniques are essential to ensure that the data used in financial news sentiment analysis is clean, structured, and meaningful. Techniques such as web scraping, sentiment lexicons, and machine learning methods such as SVM and LSTM are commonly used to improve the accuracy of predictions for stock movements.

RQ3:What are the most effective methods for analyzing the impact of news sentiment on price movements in stocks and commodities such as gold and crude oil?

Recent research has paid much attention to the influence of news sentiment on price movement in financial markets such as stocks and commodities such as gold, oil, and gas. Many methodologies have been devised to capture the relationship between sentiment and behavior in the market. In these approaches, they combine econometrics, machine learning algorithms, and the use of natural language processing (NLP) to analyze sentiment data and selectively predict price movements. This section discusses the methodologies most commonly used in this domain.

1. **Natural Language Processing (NLP) and Sentiment Analysis**
   Extracting sentiment from financial news articles requires using NLP techniques. The techniques run the spectrum of basic methods, like Term Frequency-Inverse Document Frequency (TFIDF) to advanced models like BERT (Bidirectional Encoder Representations from Transformers) [5]. When searching for terms in news articles that correlate with price movements, TF-IDF is commonly used. However, Bert is great at determining the contextual and subtle significance of financial news. Studies have shown that the sentiment of the news article can have a very large impact on stock and commodity markets, including gold [18]. These NLP based methods improve forecasting accuracy when combined with machine learning models such as Long-Short Term Memory (LSTM) networks [13]. In predicting price movements in volatile markets such as oil and gold, we have found that LSTM models are especially adept at capturing long-term dependencies in time series data [14].
2. **Deep Learning Models**
   The relationship of price movement has been analyzed using deep learning approaches, particularly LSTM networks, convolutional neural networks (CNN), and hybrid models such as CNN LSTM [64]. And since these models process sequential data, they're a great fit for time series data such as stock prices and news sentiment. This integration of sentiment data with past price data significantly improves prediction accuracy, especially in commodity markets such as oil and gold, and CNN-LSTM models capture both local and long-term features, increasing predictability in complex and volatile markets [96, 98].
3. **Generative Adversarial Networks (GANs) and Attention Mechanisms**
   GANs and transformer-based attention mechanisms have been adopted in sentiment analysis

for financial markets. Synthetic market data are generated using GANs and can be used to train models when real data is sparse [80]. The synthetic datasets improve models' accuracy and they are robust. However, attention mechanisms look at the most relevant part of market data and improve the model performance by selecting and weighing the most significant part from past prices and news sentiment [86, 98]. For instance, these techniques are especially useful for capturing fine and evolving patterns in financial data.

4. **Investor Sentiment Indices and Econometric Models**
   Combining investor sentiment indices with econometric models such as Vector Auto-Regression (VAR) models, it offers useful information on the relationship between news sentiment and market movements [14]. Such models enable analysis of how price changes are related to global macroeconomic factors such as geopolitical events and economic news and investor sentiment [91]. Furthermore, econometric models such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and its variants,such as Exponential GARCH (EGARCH), are frequently used to model market volatility and account for the impact of feeling on price movement [23]. Most importantly, these models have been used to predict the volatility of commodities such as oil and gold [32, 42].
5. **Hybrid and real time sentiment analysis model**
   The accuracy of financial market prediction is increasingly improved using hybrid models and the real-time sentiment analysis technique in volatile and fast markets. A series of approaches were used using multiple data sources and real-time sentiment data processing was used to improve predictive models. Hybrid models are based on the integration of multiple techniques, including machine learning algorithms, technical indicators, historical price data, and sentiment analysis to give a more general perspective on market behavior [65]. Through these models, the integration of sentiment across news articles, social media, and more with traditional access to financial data improves the prediction of market movements. In some cases, sentiment analysis is combined with SVM, ANN, or Random Forests when forecasting a stock price movement [99, 105]. In the same way, these hybrid approaches take into account market sentiment, integrate technical indicators such as moving averages and price trend to improve a more robust framework of stock price prediction [103]. However, hybrid models have been particularly effective in predicting stock prices where sentiment and technical factors are important. These models integrate sentiment signals with historical price trend analysis to better capture short-term market responses and long-term market characteristics, leading to more reliable and actionable predictions [101]. Previous studies have shown that integrating machine learning techniques with sentiment analysis has been shown to help better understand the complexities of the market and increase the general precision of prediction [107].
   Real-time sentiment analysis refers to the process of processing sentiment in real time and predicting price movement in short time frames (minutes to hours). This approach is especially helpful in markets with high volatility (ranging from Forex to various other markets affected by news releases and other market events) [74]. For use in high-frequency trading environments, these models can analyze real-time sentiment by extracting immediate market reactions to new information and delivering actionable insights to traders. It is important to use real-time sentiment analysis to predict short-term price movements because models can easily adapt to incoming news and adjust their predictions accordingly [90]. In this example, high-frequency sentiment analysis can be used to spot abrupt changes in market sentiment associated with geopolitical events, economic, and news an-

nouncements from corporations. Traders can make quick decisions on news sentiment based on the latest market sentiment ability, thus increasing their chance to achieve profitable trades. This approach has been shown to provide valuable insights into the immediate impact of news on market prices, which makes it particularly useful in fast-moving markets such as forex [80].

6. **Graph Neural Networks (GNNs) and Multi-Source Aggregated Classification (MAC)**
   Stock prediction models that incorporate more sentiment analysis are increasingly using Graph Neural Networks (GNNs) to improve sentiment analysis. GNNs model the relationships between stocks, to have a better understanding of how sentiments on related companies (regarding other stocks) can impact the price of a target stock [101]. This approach proves useful in any industry where companies are linked to each other because this sentiment when referring to one company can affect the price of the stock of other companies located in the same sector or supply chain [98]. The integration of sentiment analysis with GNNs allows the models to use both direct news sentiment and the broader industry context to more accurately predict. It allows for a more complete analysis of market dynamics and also contributes to a more accurate overall prediction [86].
   The Multi-source Aggregated Classification (MAC) method further improves prediction of stock price by combining sentiment data from human generated news about the target stock and related companies with technical indicators and transaction data. It consists of this multifaceted approach that takes into account broader market sentiment, including the spillover effects of news-related companies. MAC models aggregate information from multiple sources to obtain a more holistic view of factors driving price movements, considering a larger set of market signals, and showing a higher prediction accuracy compared to single-source models [104].

In conclusion, Table10 presents the main techniques and models used in financial news sentiment analysis, while Table11 highlights these models along with their key strengths and weaknesses, showing how each contributes differently to forecasting market movements. Together, they demonstrate the most suitable combination of approaches for news sentiment analysis and its impact on price movements in financial markets, including NLP-based sentiment analysis, deep learning models such as LSTM and CNN-LSTM hybrids, high-frequency sentiment analysis, as well as econometric models. When integrated into hybrid models, these methods are especially good at capturing the interactions between news sentiment and market behavior, and prediction accuracy improves for stocks, commodities such as oil, gold, and gas, and other financial assets. By utilizing these sophisticated methods, analysts are able to better comprehend and anticipate the non-linear and volatile behavior of financial markets, ultimately resulting in more insightful decision making.

Techniques	Models	References
Natural Language Processing (NLP) and Sentiment Analysis	TF-IDF, BERT, LSTM (LongShort-Term Memory)	[13, 14, 18]
Deep Learning Models	LSTM, CNN, CNN-LSTM Hybrid	[64, 69, 96, 98]
Generative Adversarial Networks (GANs) and Attention Mechanisms	GANs, Attention Mechanisms	[80, 86, 98]
Investor Sentiment Indices and Econometric Models	VAR(Vector Auto-Regressive),GARCH, EGARCH	[14, 23, 32, 42, 91]
Hybrid and Real-Time Sentiment Analysis Models	SVM, ANN, Random Forests,High-Frequency Sentiment Analysis	[65, 74, 80, 90, 107]
Graph Neural Networks (GNNs) and Multi-Source Aggregated Classification (MAC)	GNNs, MAC	[86, 101, 104]

Table 10. Overview of techniques and models used for financial news sentiment analysis and market prediction

RQ4:How do global and market-specific news sentiment drive price volatility and impact the interconnectedness of stocks and commodities (gold,crude oil) ?

Model	References	Strengths	Weaknesses
TF-IDF	[18]	Simple, fast, good for keyword relevance	Ignores context, shallow analysis
BERT	[5]	Captures contextual and semantic meaning	Requires large annotated data, high compute
LSTM (Long Short-Term Memory)	[14, 64]	Good for sequential dependencies, time-series	Needs large datasets, prone to overfitting
CNN	[96]	Extracts local features well,efficient	Limited temporal understanding alone
GANs	[80, 98]	Generates synthetic data, useful for sparse datasets	Training unstable, resource-intensive
VAR (Vector Auto-Regressive)	[14]	Interpretable, links sentiment with macro factors	Assumes linearity, poor for non-linear dynamics
GARCH	[91]	Models volatility effectively	Limited for structural breaks
EGARCH	[32]	Captures asymmetric volatility	Complex, parameter sensitive
SVM	[99]	Strong classifier for small datasets	Not scalable for large data
ANN	[105]	Flexible, learns complex patterns	Black-box, risk of overfitting
Random Forests	[107]	Handles non-linearities, robust	Less effective with high-dimensional text
GNNs	[104]	Models inter-stock/industry relations	Needs large relational data, heavy compute
MAC	[86]	Aggregates multiple signals,high accuracy	Complex integration, less interpretable

Table 11. Key models in financial news sentiment analysis with their main strengths and weaknesses.

Geopolitical risks, such as conflicts and regional instability, strongly influence commodity prices, particularly oil, because oil plays a vital role in global energy markets. Commodity prices, particularly in oil, are subject to geopolitical risks, such as conflicts and regional instability, because oil serves as an important factor in global energy markets. For example, when the COVID-19 pandemic resulted in global demand for nosediving oil as lockdowns spread throughout the world and industrial activity plunged, oil prices suffered heavy blows. Oil prices fell by 37 USD per barrel in April 2020, largely due to a sharp decline in demand [34]. Like any period of global uncertainty, gold prices surged during the pandemic as investors sought safe haven assets [19].

Price movements are also influenced by international trade policies. For example, trade wars, such as the US-China trade tensions, cause market volatility because they disrupt supply chains and believe investor sentiment. As markets react to potential disruptions to global trade, these policy changes are typically accompanied by price changes in commodities ranging from oil, to gold and other precious metals. As economic crises, such as the 2008 global financial meltdown or the more recent COVID-19 economic downturn, cause great uncertainty and anxiety, they affect all markets, from stocks to commodities. In addition, during such times, the oil and gold markets tend to have a strong spillover, whereby changes in one market (for example, oil) can cause changes in the other markets (for example, by changing stock prices) [23, 36].

It is no secret that the Ukraine war, which started in 2022, has had a major impact on global markets, but it is no more than that. Commodities such as oil and gas and stocks have also been affected. Disruptions in global energy supply chains and the corresponding changes in investor behavior were the cause of the conflict that led to large price fluctuations. Geopolitical uncertainty in Europe fueled a surge in energy prices as concerns over supply shortages intensified there, where reliance on Russian oil and gas is high. Rising crude oil and natural gas prices mirror these disruptions. Stock markets also saw increased volatility in broad financial markets, especially in the energy and defense sectors.

In the case of the European Union's sanctions on Russia, which threatened the reliability of Russia's oil and gas exports, they combined with global energy concerns to push oil prices even higher. Rising energy prices played an important role in pushing the skin into inflationary pressures and economic slowdowns, further causing market instability [10]. In addition, the war had stock market spillovers. Investors concerned about the long-term economic impact sought refuge in safety net assets, such as gold, which boosted the prices of gold. However, increases in operational costs and a pessimistic economic outlook caused stock markets, particularly those that depend on energy, to fall [25]. In sum, increasing ambiguity stimulated negative sentiment and a higher risk premium elsewhere in the asset class space [6, 19].

1. **Impact of US Monetary Policy on Asset Prices**
   The prices of assets such as gold, oil, and stocks are significantly impacted by US monetary policy, more specifically decisions made by the Federal Reserve (Fed). For example, gold tends to respond to any change in US interest rates as it is perceived as an asset of safe haven, as gold has solid reaction to changes in US economies and interest rates alike. Lowering interest rates from the Fed allows for lower opportunity cost of holding gold, which consequently causes gold prices to rise due to investors' search for safer assets during periods of economic turmoil [7]. On the other hand, a tighter monetary policy such as an interest rate hike can result in lower gold prices, since investors seek interest-bearing assets such as bonds [14].
   Changes in US monetary policy have a similar (significant) effect on oil prices. The Fed's decisions are inflation expectations and commodity demand in the overall economy. For example, when the Fed lowers interest rates, oil prices can rise as it signals an expansionary environment where the demand for energy increases [14] . Thus, an increase in rates leads to lower oil demand expectations and, consequently, to lower oil prices [25].
   However, it is not as straightforward with stocks as different sectors react differently to changes in monetary policy. An area where tight monetary policy can reduce equity prices by increasing the cost of borrowing and transferring and reducing corporate profits in sectors that are high in their capital expenditure, such as in utilities and industries [39]. However, it is possible for some sectors, especially the financial sector, to benefit from interest rate hikes, as it might trigger a rise in the profitability of lending.Table 12 shows the impact of monetary policy on the price movement of stocks ,gas and crude oil.

Monetary Policy	Gold	Oil	Stocks
Tightening	Negative (Price decrease)	Negative (Price decrease)	Negative or mixed (Depends on Sector)
Loosening	Positive (Price increase)	Positive (Price increase)	Positive or mixed (Depends on Sector)

Table 12. The impact of monetary policy on gold, oil, and stock prices

2. **Impact of Economic Reports and Corporate Earnings on Price Volatility and Market Sentiment**
   Volatility in commodities and stocks is also driven by macroeconomic news surprises, especially in GDP growth and inflation reports. Typically, positive GDP surprises tend to boost investor confidence, which in turn may help lift stock market returns. In terms of negative surprises, they can lead to a drop in stock prices in sectors that depend on economic growth [6].
   Similarly, inflation reports make a huge difference. Central banks may raise interest rates to combat inflation if it exceeds expectations, which could cause a sluggish stock market and chill commodity markets such as gold [7]. For example, when inflation expectations rise, oil prices tend to rise because traders anticipate higher demand and possible supply shortages. At the same time, stocks can fall as investors worry that central banks will tighten monetary policy [23, 35].
   On the other hand, when inflation comes in lower than expected, it often boosts market confidence. This tends to drive up stock prices and makes commodities such as gold, which investors view as a safe haven against inflation, more appealing [10].
   Corporate earnings reports signal to investors the state of the industry and specific companies. In sectors that are profitable, positive earnings surprises can push stock prices higher. In con-

trast to this, negative earnings surprises also lead to a decrease in stocks, especially in those sectors susceptible to economic variables.

These reports create significant price volatility, especially during broader economic shifts, because they shape market sentiment. For example, oil and gas prices are well known to be especially prone to market volatility when investor sentiment changes according to the US Federal Reserve policy stance [10, 25].

3. **Correlations Between Stock Prices and Commodities**

Sentiment spillovers occur when changes in sentiment in one market, such as the stock market, influence behavior in commodity markets. The correlation between stocks and commodities is shown in the table13.

- **Oil and Stocks:** Stock prices often follow oil prices, especially in the energy-heavy industries of energy, industrial, and transportation. Higher oil prices translate into higher revenue and profitability for oil producers , and hence when oil prices rise, energy stocks are likely to perform better [23, 32]. On the other hand, oil price shocks can hamper non-energy sectors in oil-importing countries because higher energy costs might create inflationary pressures.

- **Gold and Stocks**: In many ways, gold behaves like a safe haven asset, and prices tend to rise when the economy becomes uncertain or if the equity markets take a dive. Gold prices tend to rise when stock markets fall (in the context of negative economic news or geopolitical crises such as the COVID 19 pandemic or geopolitical tensions in the form of the Russia-Ukraine war) as investors attempt to protect themselves from volatility [7, 34].

In conclusion, geopolitical events, economic policies, and market-specific factors play crucial roles in driving price volatility between commodities and stocks. Understanding the interdependencies and

Stock Price Movement	Impact on Gold	Impact on Crude Oil
Increase	Negative (Investors shift to equities, reducing demand for safe-haven assets like gold)	Positive (Often linked with increased industrial demand and economic growth)
Decrease	Positive (Investors seek safe-haven assets during stock market downturns)	Negative (Often signals reduced economic activity and lower demand for crude oil)
Volatility	Positive (Uncertainty drives demand for gold as a safe-haven)	Mixed (Depends on the underlying causes of volatility, e.g., geopolitical events or economic shocks)

Table 13. Correlation between stocks and commodities

sentiment spillovers between these markets can provide valuable insights to investors and policymakers in managing risks and making informed decisions.

RQ5:How can causal inference methods differentiate between correlation and causation in the relationship between news sentiment and price movements in financial markets?

A causal inference problem is to identify whether the relationship between two variables is causal (i.e., one variable causes the other) or correlational (i.e., they move together and for no reason other than they move together). In financial markets, where news sentiment can influence asset prices, it is of great importance to differentiate between correlation and causality, and several statistical methods are used for this. These methods allow us to determine whether the price movements actually arise out of a change in news sentiment (positive or negative) or only coexist because of other factors.

1. **Granger Causality**

A statistical test most commonly used for causal inference is a test based on Granger causality. It addresses the question of whether future observations of one variable, say stock or commodity prices, can be predicted from past values of another, say news sentiment. Granger causality does not prove true causality but instead provides evidence of a predictive link. For instance, the Granger causality assessment in news research on stock price prediction has shown that sentiment changes can precede price changes, indicating that sentiment and stock prices may be causally related [1]. However, those thinking about Granger causality should be aware that it can only demonstrate temporal precedence, net, not a true cause-and-effect relationship [24].

2. **Transfer Entropy**
   Transfer entropy is another powerful tool for causal inference, based on information theory. Quantifies the flow of information between two time series, e.g. news sentiment and market prices. Unlike Granger causality, transfer entropy can also detect both linear and nonlinear relationships and is particularly useful in identifying asymmetric causality. For instance, transfer entropy could be used to uncover whether negative news sentiment leads to a larger price response than positive news sentiment, an important result of studies on commodity price prediction [9]. This presents a method for a more nuanced understanding of how news sentiment affects financial markets under changing market conditions.
3. **Asymmetric causality methods**
   Asymmetric causality methods examine the potential that the effect of positive and negative news sentiment on market prices is asymmetric. These methods, namely, nonlinear Granger Causality and Asymmetric Vector Autoregression (AVAR), are used to test whether negative news impacts the price more strongly or for a longer period of time than positive news. It is especially important during stressed markets when the impact of news could be asymmetric [17]. The impact of sentiment can be variable, depending on market conditions, including times of financial crises or high volatility, for which asymmetric causality tests can be extremely useful [46].
4. **Correlation and Causality**
   Correlation means that two variables move together, while causality means that one variable directly affects the other. A statistical relationship between two variables that tend to move in the same or opposite directions is correlation. However,it should be noted though that just because two variables correlate does not mean that one variable causes the other to change. An example would be that stock prices correlate with news sentiment, but news sentiment does not necessarily induce stock prices to go up or down [48]. It could be a relationship or it could just be unrelated. Correlation can tell us in financial markets that there is a relationship between sentiment and asset prices, but correlation alone cannot be used to make decisions without investigating causal mechanisms [33].
   On the other hand, causality implies a more strict relation, so a variation of one variable results in a variation of the other [2]. Methods like Granger causality, transfer entropy etc. are used to establish causality in the sense of whether news sentiment causes the movement towards asset prices etc [109]. For example, causal inference methods are stronger than correlation as they add directionality, i.e. changes in sentiment cause price changes and not just move together.
   There is, for example, causality in cases where news sentiment over a commodity such as oil causes its price to increase [73]. Understanding causality in the sense of financial markets is important because it will help investors make decisions about whether or not the news sentiment changes require a change in their portfolios.
   The main paradox between correlation and causality consists in the direction and nature of the relationship. Correlation, on the other hand, is reserved for monotonically quantifying the strength and direction of an association between two (or more) variables, while causality is reserved for the notion of such a relationship because it implies a directional change, that is, the change of values in one variable can (and indeed must) directly lead to the change of values in the other [74]. This distinction is very important when we are working with financial markets as a news sentiment correlation between price movements does not necessarily correlate the

sentiment to the price changes. For instance, Granger causality, transfer entropy, and VAR algorithms are used to uncover whether and how news sentiment affects financial prices, and help investors and policymakers make informed decisions. [40].

RQ6:What are the most effective evaluation met- rics for assessing the performance of sentiment analysis models in predicting price movements in financial markets?

Significant number of evaluation metrics are used by researchers and practitioners in evaluating the performance of sentiment analysis models to effectively predict price movement in the financial market. These metrics are intended to evaluate the quality of sentiment classification along with the precision of prediction of market movements using sentiment, in the context of a time series.

1. **Accuracy**
   Accuracy measures the percentage of correctly predicted outcomes relative to all predictions. It is the ratio of correct predictions to the total number of predictions.

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalnumberofPredictions} \quad (1)$$

   Yet in the realm of financial markets, especially when trying to use sentiment analysis to forecast stock, commodity, or FX prices, accuracy is not a measure that should be pinned. There are imbalances in financial data: most price movements are neutral or insignificant, and only a few major movements qualify as noteworthy [105]. A model that just guesses that there are no significant changes every time is likely accurate, without offering any useful predictions for market decisions. Therefore, accuracy alone is not enough to evaluate the performance of sentiment analysis models in this domain [106].

2. **Precision and Recall**
   For tasks where prediction of positive or negative market movement matters, accuracy limitations can be mitigated through the use of metrics such as precision and recall. The correctness of positive predictions is taken by precision. In other words, it measures the proportion of correctly predicted positive sentiment or price movement (such as upward or downward trends) of all predicted positives [42].

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \quad (2)$$

   High precision indicates that when the model predicts positive sentiment or a price increase, it is likely correct. This is important when predicting significant price movements, where a false prediction could lead to substantial losses [2].
   Recall, on the other hand, measures the model's ability to identify all actual positive cases. It is the ratio of correctly predicted positive sentiment or price movement to all actual positive cases.

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \quad (3)$$

   Recall is important in sentiment analysis for financial prediction as it guarantees that the model can pick up all instances where sentiment or price movement is important. For example, suppose that a model that forecasts upward price movement but fails to capture actual upward movements would have a low recall, so it would miss trading opportunities [69].
   F1 score is often used because precision and recall work counter to each other (i.e. increasing one may decrease the other, relating in a holistic way).

3. **F1-Score**
   The F1 score is the harmonic mean of precision and recall, offering a balanced evaluation metric that is especially useful when there is an uneven class distribution or when false positives and false negatives have different costs [103].

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

   F1-score offers more reliable measure of model performance than accuracy alone for financial market prediction, where overestimating and underestimating market movements are costly. Specifically, a model with a higher F1 score would get better at fewer mistakes and predict a significant trend acting better [59].

4. **Mean Absolute Error (MAE)**
For regression-based models that predict actual market prices or price changes based on sentiment analysis, Mean Absolute Error (MAE) is widely used [97]. It measures the average of the absolute differences between the predicted prices and the actual prices.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{5}$$

Here, $\hat{y}_i$ is the predicted value and y_i is the actual value. MAE is simple to use with an easy-to-understand metric; smaller MAE values are indicative of better predictive performance. However, it does not offer a penalty for large errors over small ones, which limits it to forecasting volatile financial markets [75].

5. **Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)**
Both MSE and RMSE are used to measure the average squared differences between the predicted and actual values. These metrics are more sensitive to large errors than MAE, as they square the residuals [67]

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{6}$$

$$RMSE = \sqrt{MSE} \tag{7}$$

MSE is useful in identifying models with particularly bad predictions, but is rarely used in financial market prediction tasks, as RMSE retains the units of the values to be predicted to facilitate financial decision making. This is particularly important when we are dealing with volatile assets such as stocks, commodities, cryptocurrencies, etc., as large prediction errors can mean significant financial losses [88]. The lower the value of the RMSE value means that the model is better predicting and vice versa, if the value is large, then the model has greater problems with prediction [22].

6. **Time-Series Specific Metrics**
In time series prediction tasks, such as forecasting stock prices or commodity values, cross-validation techniques like rolling window cross-validation are applied to simulate real world situations where past data is used to predict future results [27]. At the same time, this approach measures how much the model learns over time, because market dynamics change continuously.
Moreover, out-of-sample prediction performance, i.e., how good a model is at predicting data that was not used to train the model, is of paramount importance for judging how a model would behave in the case when there is unseen data. In financial markets, past data may not be enough to influence future conditions [100].

7. **Computational Efficiency and Training Time**
In the context of deep learning models such as LSTM, BERT, and Transformer-based approaches, training time efficiency and computational cost also play a significant role. Financial markets require real-time or near-real-time predictions, which means that the model must not only perform well in terms of accuracy but also speed and scalability [83]. The time complexity of models such as LSTM or BERT can be significant, and models that require high computational power may not be practical for real-time stock trading [101].

In summary, the most effective evaluation metrics for sentiment analysis models in financial market prediction are a combination of F1-score, RMSE, precision, and recall, along with time-series-specific metrics and computational efficiency considerations. These metrics ...ensure that sentiment analysis models remain accurate and efficient for real-time market decision-making.

RQ7:What are the limitations in current research on applying sentiment analysis techniques to financial news for predicting asset prices

The table14 presents a detailed summary of various research papers on stock market prediction using news sentiment analysis and machine learning algorithm.The table highlights each paper's limitations and suggested future directions, showing the continuing difficulties and opportunities in this area. Common limitations include manual categorization of data, high computational needs, lack of model adaptability for different industries, and market conditions. Generally, future research on such models is focused on improving their efficiency, utilizing more sophisticated natural language processing (NLP) models, including transformers, and utilizing other sources of data including social media and real-time news. It shows that sentiment analysis models need to be refined and their ability to generalize better for better prediction accuracy and real- time stock market forecasting. Table14 provides some of those insights into the highly dynamic nature of this area of research and how much more can be done.

4 Taxonomy

Figure 4 shows the taxonomy of the important aspects in financial news sentiment analysis and market prediction. It includes a description of the various markets being analyzed, stocks, gold, crude oil, etc., and a description of the techniques being used, NLP approaches, deep learning models, and a list of hybrid methods. Covers fundamental processes including data collection, creating dataset, annotation, as well as problems of data imbalance and noise. In addition, it details the effect of news sentiment on asset prices, volatility, and market spillover effects. Lastly, challenges, limitations, and future research directions are posed by identifying multilingual datasets, real-time analysis, and advanced causal inference methods.

5 Key Findings and Discussion

In recent years, sentiment analysis techniques have been applied to financial news to predict asset prices. Several studies have tried to determine whether the use of sentiment from news sources helps predict market movements. One way to approach the data is to use advanced machine learning (ML) models, like deep learning architectures like LSTM, and CNN, to process sentiment rich data for financial decision making. For instance, Usmani et al. proposed a weighted and categorized news stock prediction model based

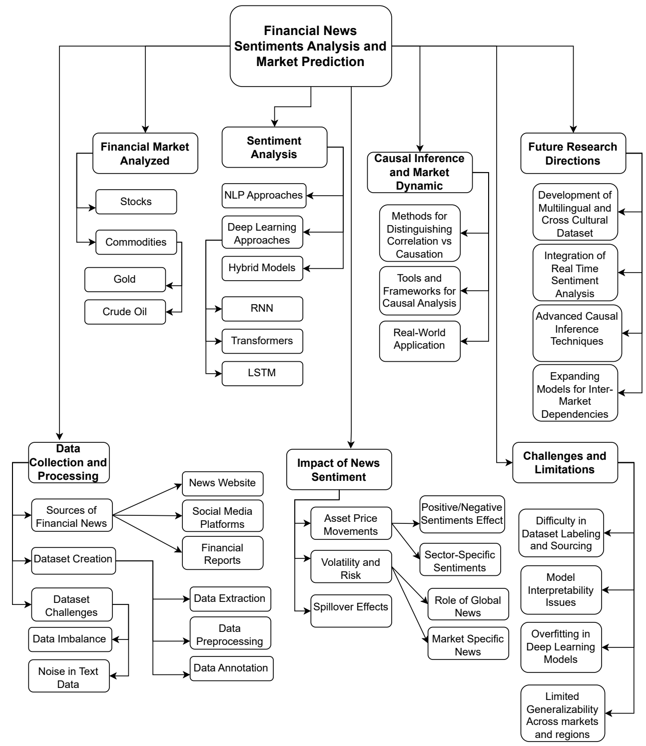

Figure 4. A Taxonomy of Financial News Sentiment Analysis for Market Prediction

on the use of weighted news categories given their relevance, which improves with the forecast accuracy [50].This is in agreement with the high consensus that categorizing news in relevant sectors such as market, sector, and stock news enables better prediction results [7].

Although this improvement has been made, still some limits exist. The first challenge is the complexity and volatility of the financial markets, making it difficult to make accurate predictions [106]. Sentiment analysis techniques, however, have yet to demonstrate their full potential, as they are frequently hindered by problems of noisy data, subjective sentiment interpretation, and nonstationarity of financial time series [32].

Furthermore, sentiment in unstructured data from sources such as social media and financial news is challenging to incorporate. Upon analyzing different studies, some trends emerge. So far, traditional sentiment analysis tools and simpler ML models

Ref	Paper Title	Limitations	Future Directions
[11]	A novel approach to Predict WTI crude spot oil price: LSTM-based feature extraction with Xgboost Regressor	The model has an intricate architecture and requires significant processing time, which can be a challenge for real-time applications.	Future research could focus on developing models that use lower processing resources while maintaining comparable levels of precision. It is also suggested to incorporate more extensive datasets and additional geopolitical/macroeconomic factors, like OPEC decisions, to improve model accuracy.
[108]	Development of a CNN-LSTM Approach with Images as Time-Series Data Representation for Predicting Gold Prices	The prediction model may not be generalizable across different time periods or markets.	Future research should incorporate a wider range of datasets and timeframes, and integrate more external economic indicators for improved performance?
[18]	Oil price volatility and new evidence from news and Twitter	Media sentiment from Twitter and news may not always reflect true sentiment, and results may vary depending on the platform used.	Future research should examine the impact of news across various platforms and focus on real-time data for volatility forecasting?
[106]	Sentiment Analysis of Financial News and its Impact on the Stock Market	The model's ability to predict stock movements is limited by the accuracy of the sentiment analysis and the quality of the news data.	Future directions include improving sentiment analysis techniques and incorporating additional data from diverse sources, including social media?.
[85]	Predicting the Effects of News Sentiments on the Stock Market	The model is dependent on the quality and reliability of the news sentiment data, which may not always accurately reflect market sentiment.	Future work should focus on developing better sentiment analysis tools and integrating more varied data sources to improve prediction accuracy?
[97]	Stock Price Prediction Using News Sentiment Analysis	The models performance can be influenced by the quality and availability of news data.	Future research could enhance the model by integrating machine learning algorithms with real-time data and improving its generalization ability?.
[105]	Efficacy of News Sentiment for Stock Market Prediction	The predictive power of news sentiment can be impacted by noisy data and biases in sentiment interpretation.	Future work could explore advanced machine learning techniques and focus on real-time prediction systems for improving accuracy?
[50]	News Headlines Categorization Scheme for Unlabeled Data	The approach requires manual selection of seed keywords, which limits its scalability and automation.	Future work could focus on automating the process of keyword selection and refining the categorization technique to handle larger datasets?.
[48]	News-driven stock market index prediction based on trellis network and sentiment attention mechanism	The model requires a considerable amount of data and computation, making it difficult for real-time applications.	Future research could explore reducing computational complexity, enhancing the models real-time applicability, and investigating the impact of news sentiment in different market conditions?.
[70]	News-based intelligent prediction of financial markets using text mining and machine learning	Existing models are not fully leveraging advanced language models like transformers, limiting their ability to capture deeper contextual meanings from news data.	Future directions include integrating more sophisticated NLP techniques like BERT and focusing on enhancing model adaptability across different markets?.
[58]	Stock Price Prediction using Zero-Shot Sentiment Classification	The model's reliance on social media data introduces potential biases, and its effectiveness may vary across different industries.	Future work should aim to incorporate multiple data sources, including diverse financial news and real-time data, and further refine sentiment classification techniques?.
[69]	A sentiment analysis-based machine learning approach for financial market prediction via news disclosures	The model is limited by the complexity of natural language and may not perform well with highly ambiguous or conflicting news.	Future research could work on improving the models robustness to ambiguous data and exploring the use of larger, more diverse datasets to increase accuracy?.
[80]	Enhancing stock price prediction using GANs and transformer-based attention mechanisms	The models reliance on GANs and attention mechanisms may lead to overfitting and unrealistic data generation	Future work should explore regularization techniques and the integration of more external data sources to improve prediction accuracy and generalization?.
[60]	Predictive Precision: LSTM-Based Analytics for Real-time Stock Market Visualization	The high volatility of stock data makes it challenging to achieve consistently high prediction accuracy.	Future directions could involve improving data preprocessing methods and enhancing model adaptability to different market conditions?.
[85]	Predicting the Effects of News Sentiments on the Stock Market	The sentiment analysis model is limited by the quality and granularity of the news data, which may not fully capture market sentiment.	Future research could focus on improving sentiment classification techniques and integrating social media data for more dynamic and real-time predictions?.

Table 14. limitations and proposed future directions in financial news sentiment analysis for market prediction

have succeeded in predicting short-term changes in stock movement [65].The application of deep learning models such as LSTM and CNN has greatly improved prediction accuracy by handling the complexity of financial data [86]. As seen, for instance, in Liu et al.'s work, introducing a sentiment attention mechanism together with LSTM and CNN results in a stock market index prediction model with improved ability to predict market conditions using sentiment analysis [48].

Unfortunately, however, gaps in the literature exist. However, many current studies are still challenged by data scarcity and high computational costs in large-scale sentiment analysis. Furthermore, news sentiment is spatially dependent on market dynamics rather than being merely a function of the latter, with complex relationships between news sentiment and market dynamics difficult to model using traditional models in environments such as the financial crisis [32].

Research on spillover effects of oil price volatility on stock markets requires more robust models that can handle such an extreme case [87]. Although improvements in sentiment analysis present an attractive avenue of strength for improving stock market prediction models, there are evident challenges concerning data quality and scalable models. Consequently, future studies could improve sentiment analysis techniques by combining advanced NLP methods with the use of real-time data to improve decision making.

6 Challenges and open Issues

Sentiment analysis applied to financial news to predict asset prices is hampered by several major obstacles, which many other studies have identified. First, there is the problem of the creation and availability of high-quality datasets. Most researchers point out that sentiment datasets tend not to be easily accessible, nor are they complete, outdated, or not suitable for the domain under investigation. For example, if there are not enough data that accurately mimics market sentiment, then sentiment analysis may not be able to correctly predict financial movements. For instance, in studies such as those of Banerjee et al. and Chi et al., the sentiment from the coverage of news of commodities or stocks may not necessarily represent the entirety of investors' reactions, when the content of the news is ambiguous or contradictory today [22, 24].

Another tough problem is news classification. News classification into appropriate categories and the ability of sentiment analysis tools to properly infer news sentiments are both tough tasks. Although sentiment lexicons can be helpful, in many cases they do not capture nuances or context-specific sentiments in financial news, and many research studies still rely on them [59]. In addition, news about related companies or broader market events can have a strong influence on the price of a target stock, but traditional models usually focus on direct company-specific news [98].

Research also has difficulties with the causality between news sentiment and asset prices. Many of the studies had demonstrated a correlation between sentiment and moves in price, yet causality is a more elusive topic. However, many models make the assumption that sentiment directly influences price movements, but not always other factors, such as market manipulation, economic reports, and geopolitical events, also have an influence too [44].In volatile markets such as cryptocurrency, news sentiment may have an exaggerated or delayed impact on which clear causal relationships must be established to improve the reliability of predictions [65].

Furthermore, market volatility and the presence of misinformation (fake news or media hype) make the power of sentiment analysis for prediction even harder. Ewald et al. and Banerjee et al. note the increasing power of hype and fake news in the media, particularly in times of market stress, such as in the case of the COVID 19 pandemic [13]. They can lead to inappropriate price predictions or investor overreactions.

In addition, sentiment analysis models are neither interpretable nor transparent. Advanced deep learning techniques, such as LSTM and CNN, have occasionally achieved the promise of improving prediction accuracy, but have unfortunately also been criticized for being "black-box" models [88]. This opaque process makes it difficult for investors and researchers to understand the behind the curtain decision-making process in these models, and ultimately makes adoption into real-world trading decisions difficult [5].

However, the domain of financial sentiment analysis faces issues of data quality, network and item information, news classification, causal inference, market volatility, misinformation, and model transparency. To increase the predictive power and reliability of sentiment analysis in financial decisions, the issues mentioned will need to be addressed using more robust models and with different data sources.

7 Future Directions

Future research in financial news sentiment analysis will shift toward more reliable and context-sensitive methodologies that go beyond basic sentiment classification by integrating causality-driven models, real-time data processing, and advanced machine learning techniques such as training transformer-based models like DeBERTa on large-scale financial news corpora. These models can then be used for feature extraction and sentiment/event classification tasks, maintaining high accuracy and contextual relevance in volatile markets. A major focus will be on developing expert-annotated financial news datasets built from headlines and descriptions collected across multiple financial news websites. These datasets should not only classify news sentiment, but also use the detailed descriptions to extract key economic or geopolitical events and annotate them accordingly, while establishing a direct connection with historical price movements, offering deeper insights into actual market impact. Existing sentiment-based datasets, such as those used in stock market prediction , often rely on polarity-based labeling (positive, negative, neutral) without accounting for causal relationships or expert judgment, leading to unreliable predictions. Automatic sentiment classification, while useful, lacks the ability to distinguish between correlation and causation, making it less effective for financial forecasting. To address this, domain experts, supported by NLP pipelines, should carefully annotate future datasets. These pipelines can extract key events such as geopolitical tensions, monetary policy shifts, or supply chain disruptions from news descriptions, while experts ensure accuracy and contextual relevance. To further improve reliability, the annotated labels should be validated against short-term and long-term market reactions, particularly for assets like gold and crude oil where price movements often result from multiple interdependent factors. Moreover, research should emphasize the creation of dynamic, real-time datasets that integrate these annotations with live market data and macroeconomic indicators, ensuring adaptability to evolving market conditions and stronger predictive power for high-stakes financial forecasting.

Furthermore, apply multimodal data fusion where sentiment features are merged with quantitative indicators (interest rates, volatility indices, and commodity supply data) using feature-level fusion techniques, improving prediction robustness. This approach may help improve the accuracy and predictive power of sentiment analysis models.Transformer-based architectures such as FinBERT and DeBERTa, when fine-tuned on large-scale annotated financial news corpora, will play a pivotal role in sentiment analysis, with future advancements focusing on adaptive and dynamically evolving models that continuously update as new financial events unfold.Large Language Models (LLMs), such as GPT-based architectures, can be fine-tuned on annotated financial event–price datasets to detect and categorize emerging financial news patterns. When integrated into agentic AI agents, these models can autonomously analyze incoming news streams, cross-check sentiment with live market data, and adapt predictions in real time, ensuring that forecasts remain accurate and contextually relevant as market sentiment drivers evolve. Rather than treating sentiment classification as a static task, future research should take advantage of Natural Language Processing (NLP), reinforcement learning, and neural networks to develop more sophisticated and context-sensitive models. These models should not only classify sentiment, but also quantify the intensity of its impact on asset prices, particularly for stocks, gold, and crude oil.

In summary, future directions in the field of financial news sentiment analysis will revolve around the integration of causal inference methods, the development of dynamic real-time datasets, the use of advanced machine learning models, and the ensured model transparency. This approach will provide deeper insights into how financial news drives market behavior, providing more reliable tools to predict asset price movements.

8 Conclusion

In conclusion, the field of financial news sentiment analysis for predicting asset prices has witnessed significant advances, with numerous studies that use machine learning, deep learning, and natural language processing (NLP) techniques. However, despite progress, several challenges persist, particularly those related to dataset quality, news classification, and the establishment of clear causal relationships between news events and market movements. Many existing models focus on sentiment classification, yet they often overlook the deeper causal mechanisms driving financial markets. These limitations need to be addressed in future research, which should include causality-based models to separate between true causal relationships and simple correlations. Researchers can develop more accurate and reliable financial news sentiment analysis by integrating real-time dynamic datasets using a multimodal data fusion from multiple sources such as social media, financial news, and macroeconomic indicators. Furthermore, the impact of misinformation and media hype in distorting market reactions in particular in financial uncertainty should not be underestimated. This demonstrates a need for models that not only predict but are also transparent so that stakeholders can trust the predictions and know how the underlying mechanisms are occurring.

Ultimately, the future of financial news sentiment analysis lies in the development of adaptive, interpretable, and causality-driven models. By embracing these advanced methodologies, researchers can enhance the predictive power of sentiment analysis tools and provide more valuable information to academics and practitioners in financial markets. As the financial landscape continues to evolve, these advances will play a crucial role in guiding investment decisions and improving market efficiency.

Conflict of interest statement

The authors declare no conflict of interest related to the content of this study. The research was conducted independently, without any financial, commercial, or personal relationships that could influence the outcomes or interpretations presented. All findings and conclusions are based solely on the evidence reviewed and analyzed in this study.

Ethics statement

No human or animal subjects, nor sensitive personal data, are involved in this study. Research is grounded on a systematic review of literature, which is publicly available and conforms to ethical guidelines of secondary data analysis. Every study referenced was properly cited, and every effort was made to avoid plagiarism or misrepresentation of the findings. The ethical principles of academic integrity are adhered to in this work, and the intellectual property rights of the original authors are respected.

Authors Contribution

Aqsa Ehsan and Shaista Habib: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration and Visualization. **Shaista Habib:** Supervision, Validation. **Aqsa Ehsan, Shaista Habib and Arman Sohail:** Writing—Review and Editing. **Aqsa Ehsan and Shaista Habib :** Contributed equally to this paper as first author. All authors have read and agreed to the published version of the manuscript.

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