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ANALYZING SOCIAL MEDIA SENTIMENT TOWARD SPECIFIC COMMODITIES FOR FORECASTING PRICE MOVEMENTS IN COMMODITY MARKETS

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ABSTRACT

This study adopts a systematic literature review to analyze social media sentiment towards specific commodities to enhance the accuracy of price movement forecasts in commodity markets. Drawing from the field of applied mathematics, the research gathered literature from Scopus, DOAJ, and Google Scholar databases, covering publications from 2014 to 2024. A rigorous search strategy yielded 66 journal articles, with 30 being selected for their close relevance to keywords such as "social media sentiment," "commodity markets," and "price forecasting." Results indicate that social media sentiment significantly influences commodity prices, with particular variations based on commodity type and geographical context. Specific sentiment factors—especially intensity, polarity, and timing—were found to have a pronounced impact on price dynamics, with sentiment polarity being particularly influential in volatile markets. Additionally, advanced analytical methods, like Bayesian Dynamic Linear Models and LSTM neural networks, enhance predictive accuracy when applied to sentiment analysis in this context. These findings underscore the value of social media sentiment in refining forecasting models, while also highlighting gaps in understanding regional sentiment variations and their effects on different commodity types. By synthesizing these insights, this study emphasizes the importance of considering social media sentiment for more accurate price predictions and identifies key areas for future research to explore the multifaceted impacts of sentiment in commodity markets.

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1. INTRODUCTION

Commodities play a pivotal role in the dynamics of the global market [1]. As primary resources underpinning economic activities, commodities exert a far-reaching impact on global economic stability and international trade. The commodities sector, encompassing various products such as oil, metals, and agricultural produce, serves not only as a cornerstone for major industries but also as the foundation for supply chains spanning across national borders. Price movements in commodities garner significant attention due to their influence on inflation rates, economic growth, and the financial stability of nations [2]. However, determining commodity prices is no straightforward task, given the complexity of influencing factors. Apart from fundamental factors like supply and demand, social sentiment also wields considerable influence in price determination. The evolving opinions and perceptions on social media can sway market attitudes toward a particular commodity, potentially leading to substantial price fluctuations and market volatility [3]. Hence, a profound understanding of social sentiment becomes increasingly crucial in anticipating, analyzing, and responding to commodity price movements effectively within the dynamic global market.

The role of social media in shaping public opinion and sentiment across various facets of life is paramount [4]. Within the realm of market analysis, social media has emerged as a significant source of information, providing profound insights into market behavior patterns and trends. The widespread use of social media among the populace sees millions of individuals actively engaging and exchanging information daily. In market analysis, social media platforms offer a continuous stream of data concerning consumers' perceptions, opinions, and attitudes toward specific products and services [5]. This information can be comprehensively analyzed to identify trends and sentiments that may influence market behavior. The sentiments evolving on social media platforms hold substantial potential to swiftly and significantly impact market behavior [6]. The dissemination of positive or negative opinions or impressions regarding a product or brand on social media can trigger chain reactions among consumers, ultimately influencing purchasing decisions and market performance. Therefore, understanding and analyzing the sentiments emerging on social media platforms are crucial in responding to and anticipating potential shifts in market behavior.

The conventional methods of analyzing commodity markets have long served as a foundation for understanding market dynamics [7]. These approaches typically rely on fundamental factors such as supply and demand, global economic conditions, and geopolitical factors. While their contribution to understanding commodity markets has been significant, their limitations are becoming increasingly evident. These limitations are particularly noticeable in their inability to accurately predict future commodity price movements. The increasingly complex market conditions, including high volatility and the influence of non-traditional factors, pose challenges to the predictive accuracy of these conventional methods [8]. In an era where social media has become the primary stage for various discussions and interactions among the public, the importance of seeking new methods that can incorporate non-traditional factors such as social media sentiment is becoming more apparent. Sentiments expressed on social media can provide valuable insights into market perceptions and attitudes toward a particular commodity [9]. Therefore, seeking approaches that can integrate information from various sources, including social media sentiment, is a crucial step in enhancing the accuracy of commodity market analysis and predicting price movements in the future.

Social media sentiment analysis plays an indispensable role in forecasting fluctuations in commodity prices through the integration of sentiment data sourced from platforms such as Twitter into market analysis frameworks. Scholars have effectively employed sentiment analysis methodologies to anticipate shifts in oil prices [10], assess public reactions to governmental policies influencing fuel costs [11], and predict trends in commodity markets by integrating economic principles and societal insights gleaned from platforms like Google Trends [12]. Empirical investigations have evidenced that sentiment analysis enhances the precision of predictive models, thereby augmenting their efficacy [13]. Leveraging machine learning algorithms such as Naïve Bayes and AdaBoost, sentiment analysis facilitates the classification of public sentiments as either positive or negative, thus facilitating predictions regarding market trends [14]. Furthermore, specialized affective models tailored to specific domains, such as CrudeBERT and CrudeBERT+, have exhibited superior predictive capacities in analyzing sentiments within the crude oil market [15].

Our study is dedicated to examining social media sentiment concerning specific commodities with the objective of refining the accuracy of market price predictions. The selection of commodities for scrutiny holds significance owing to the substantial influence of social sentiment on market dynamics [16]. Through an exploration of sentiment analysis on commodities such as fuel oil (BBM) and cryptocurrencies like Bitcoin and Ethereum, we aim to capitalize on insights derived from social media interactions to enhance the precision of predicting price fluctuations [17]-[18]. The comprehension of public opinions and emotions concerning these commodities via sentiment analysis facilitates the acquisition of valuable data for honing market forecasts and facilitating informed decision-making [19]. This methodological approach empowers us to harness the potential of social media sentiment in refining the accuracy of forecasting market prices and trends.

The research conducted by Uchtenhagen [20] and Coibion [21] both contribute significantly to elucidating consumer behavior and its correlation with external stimuli. Uchtenhagen's investigation into addiction treatment policy and research underscores the criticality of considering risk factors and treatment objectives, elements that may bear relevance in comprehending the potential impact of social media sentiment towards commodities on consumer behavior. Coibion's inquiry into the ramifications of inflation expectations on consumption decisions presents a methodological framework that holds promise for examining the influence of social media sentiment on movements in commodity prices. These studies, in conjunction with the insights provided by Collis [22] regarding the consequences of limiting social media usage, collectively suggest that while social media can exert a profound influence on consumer behavior, understanding its specific implications on commodity price fluctuations necessitates further scrutiny and exploration.

Based on the synthesis of existing research, several gaps remain unaddressed that align closely with this study's objectives of analyzing social media sentiment toward specific commodities to improve the forecasting of price movements in commodity markets. Firstly, there is limited understanding of how social media sentiment specifically influences the price dynamics of distinct commodities, such as fuel oil and cryptocurrencies, despite general findings that sentiment affects commodity prices. Secondly, the relationship between social media sentiment and commodity market behaviors across various geographical contexts is underexplored, as most prior studies primarily examine global commodity markets without investigating regional variations in social sentiment and their impact on local or regional commodity price trends. This creates a gap in understanding how geographical factors might mediate or moderate the sentiment-price relationship. Additionally, there is a lack of research specifically attempting to identify distinct factors within social media sentiment, such as sentiment intensity, polarity, and subject, that significantly impact commodity prices. While general sentiment has been shown to influence commodity markets, the absence of targeted analysis on specific sentiment factors limits precise forecasting insights. This study seeks to address these knowledge gaps through a systematic literature review approach, employing advanced methodologies to explore the intricate relationship between social media sentiment and commodity price fluctuations. To analyze sentiment, clustering methods such as Bayesian Dynamic Linear Models and Probabilistic Approaches are utilized to classify sentiment into categories like positive, neutral, and negative, offering insights into how different types of sentiment impact commodity prices. For forecasting purposes, time series methods such as Geometric Brownian Motion and Long Short-Term Memory (LSTM) Neural Networks are used to model and predict price trends with enhanced accuracy. Additionally, to identify the most impactful sentiment factors, statistical techniques like regression analysis and causal inference are applied, allowing for a detailed examination of sentiment intensity, timing, and type in relation to commodity market behavior. By leveraging these advanced approaches, this research aims to contribute to more accurate prediction models and deepen the understanding of commodity market dynamics across diverse regions.

2. RESEARCH METHODS

This study adopts a qualitative research approach, utilizing a systematic literature review to investigate the analysis of social media sentiment towards specific commodities and its implications for forecasting price movements in commodity markets. Therefore, this research focuses on the field of applied mathematics, employing various mathematical methods such as Bayesian Dynamic Linear Models, Long Short-Term Memory (LSTM) Neural Networks, Ensemble Empirical Mode Decomposition (EEMD), Geometric Brownian Motion, and Random Forest to quantify and interpret the relationships between social media sentiment and commodity price movements. In conducting the literature search, a rigorous strategy was employed. Academic databases such as Scopus, Directory of Open Access Journals (DOAJ), and Google Scholar were systematically searched using a combination of keywords such as "social media sentiment," "commodity markets," and "price forecasting". To complete this research, the researchers collected a total of 66 journal articles. From these, 30 articles closely related to the keywords used were selected. Boolean operators were applied to refine search queries, ensuring the retrieval of relevant articles. Additionally, manual searches of reference lists were conducted to augment inclusivity. The search was delimited to articles published in English within the past decade to focus on recent and pertinent research.

Inclusion criteria for article selection encompassed studies that delve into social media sentiment towards specific commodities, explore its correlation with price movements in commodity markets, and utilize qualitative or mixed-methods approaches for sentiment analysis. Furthermore, selected literature should be peer-reviewed and available in full text. Exclusion criteria entailed non-peer-reviewed sources, studies unrelated to social media sentiment analysis or commodity market forecasting, articles not accessible in full text or written in languages other than English, and publications predating the last decade. The selection process involved screening titles and abstracts to gauge relevance to the research topic. Full-text articles meeting inclusion criteria were retrieved and subjected to detailed review. Pertinent data, including authorship, publication year, research methodology, key findings, and conclusions, were systematically extracted from each selected article. Data extraction was executed meticulously to ensure accuracy and comprehensiveness. Extracted data were then synthesized and analyzed to identify trends, patterns, and gaps in existing research, thereby informing the discussion and conclusions of the systematic literature review. Based on this explanation, the procedure of this research can be seen in Figure 1.

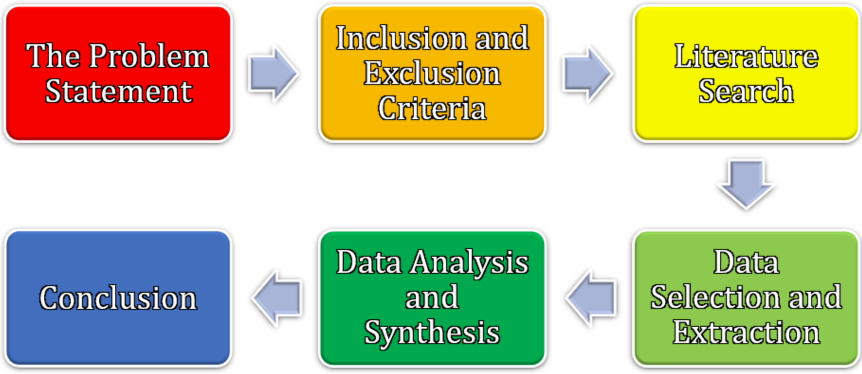

Figure 1. Research Procedure Utilized

3. RESULTS AND DISCUSSION

Based on the search results from 66 journal articles, 30 relevant research findings have been identified that can elucidate the focus and objectives of this study. We have formulated several aspects that need to be explained, including: (1) The Relationship between Social Media Sentiment and the Movements of Specific Commodities Prices in Commodity Markets; (2) Patterns or Trends that can be Identified from Social Media Sentiment toward Specific Commodities; (3) The Influence of Positive and Negative Sentiment on Social Media on Commodity Price Movements; (4) Variance in the Impact of Social Media Sentiment on Various Types of Commodities: Energy, Metals, and Agricultural Commodities; (5) Effectiveness of Various Sentiment Analysis Methods in Predicting Commodity Price Movements; (6) Factors Within Social Media Sentiment That Exert a Greater Influence on Commodity Price Movements; (7) Implications of Findings on the Development of More Accurate Price Prediction Models and Trading Practices in Commodity Markets.

Table 1. Focus and Insights into Research Results According to Eligibility Criteria

No.	Focus and Scope	Authors	Insight or Research Variables Discussed
1.	Social Media Sentiment and Commodity Price Movements	W. Liu et al. (2023), N. Yang et al. (2023)	Impact of sentiment on volatility and returns
		Kaplan et al. (2023), Chen et al. (2021)	Sentiment as predictor, affective models
		Khadjeh Nassirtoussi et al. (2014)	Public perceptions, market reactions
2.	Sentiment Analysis and Specific Commodities	Mayuriben et al. (2021), Sohi et al. (2023)	GMOs, cryptocurrencies, sentiment trends
		Batrinca & Treleaven (2015), Wolfert et al. (2017)	Energy, agricultural produce

No.	Focus and Scope	Authors	Insight or Research Variables Discussed
3.	Impact of Social Media Sentiment on Price Movements	Zheludev et al. (2014), Aggarwal (2022)	Prediction of returns, asymmetric response
		Rodríguez-Ibánez et al. (2023), Stankevich (2017)	Influence on market dynamics, price changes
4.	Variation in Sentiment Effects Across Commodity Categories	Yilmaz et al. (2022), Bukovina (2016)	Energy, metals, agricultural commodities
		Cooper & Gutowski (2017), Jones & Hiller (2017)	Impact of sentiment on specific markets
5.	Sentiment Analysis Methodologies in Price Prediction	Kaplan et al. (2023), An et al. (2023)	Integration with economic theory, ML models
		Shang & Hamori (2023), Xu & Hsu (2022)	Emotional scores, news-based indices
6.	Factors Influencing Social Media Sentiment Effects	Vences et al. (2020), Siegrist (2021)	User engagement, trust, external contexts
		Almeida & Gonçalves (2023)	Dissemination of negative news, emotions
7.	Advanced Techniques in Commodity Price Prediction	Ke et al. (2023), Gowthaman et al. (2023)	EEMD, LSTM, deep learning models
		Y. Liu et al. (2022), Sellamuthu (2014)	Geometric Brownian Motion, refining models
8.	Bias Recognition and Mitigation in Price Prediction	Todd et al. (2019), Dakin et al. (2020)	Patient-level simulation, bias identification
		Wang et al. (2019), Coibion (2022)	Generalizability, impact of monetary policy

Table 1 summarizes research findings in the field of social media sentiment analysis and its impact on commodity price movements, categorizing them into eight main areas of focus. The first focus area revolves around the relationship between social media sentiment and commodity price volatility and returns, with the authors highlighting the predictive capabilities of sentiment analysis models. The second area discusses sentiment analysis applied to specific commodities, such as cryptocurrencies and genetically modified organisms (GMOs), emphasizing the insights gained into public perceptions and market reactions. The third area explores the influence of social media sentiment on price movements, including its role as a predictor and its asymmetric response effect. The fourth area examines the variation in sentiment effects across different categories of commodities, highlighting the nuanced dynamics within energy, metals, and agricultural markets. The fifth area discusses various methodologies and techniques used in sentiment analysis for predicting commodity prices, focusing on integrating economic theory and machine learning models. The sixth area identifies factors influencing the effectiveness of social media sentiment, including user engagement and the dissemination of negative news. The seventh area showcases advanced techniques in commodity price prediction, such as ensemble empirical mode decomposition (EEMD) and deep learning models, to enhance forecasting accuracy. Lastly, the eighth area addresses bias recognition and mitigation in price prediction models, emphasizing the importance of statistical rigor and generalizability. Overall, these research findings underscore the significance of social media sentiment analysis in informing market decisions and enhancing the predictability of commodity price movements.

3.1 The Relationship between Social Media Sentiment and the Movements of Specific Commodities Prices in Commodity Markets

Social media sentiment emerges as a pivotal factor in forecasting price fluctuations within commodity markets. Empirical investigations reveal that sentiment analysis derived from platforms such as Twitter and Sina Weibo possesses the capability to influence the volatility of cryptocurrency prices [23]. Furthermore, the sentiment prevailing within social networks emerges as a significant predictor of returns on commodity futures, thereby shaping investor strategies and market outcomes [24]. Particularly noteworthy is the pronounced interconnectedness between sentiment and market volatility, particularly evident during periods of economic turbulence, wherein sentiment indices transition from passive receivers to active transmitters of shocks [25]. Additionally, specialized affective models tailored to specific domains, exemplified by

CrudeBERT+, have been devised to integrate economic principles and social insights sourced from Google Trends, thereby exhibiting superior predictive performance in anticipating movements in WTI crude oil futures prices compared to other sentiment analysis models [26]. Collectively, social media sentiment emerges as a valuable instrument for comprehending and potentially prognosticating price dynamics within commodity markets. The relationship between social media sentiment and the movements of specific commodities in commodity markets is an intriguing area of study in modern market analysis [15]. Social media sentiment can provide valuable insights into how markets react to various factors, including news, trends, and recent events that affect the supply and demand of commodities. By analyzing sentiment posted on social media platforms such as Twitter, Facebook, and Reddit, researchers can identify specific patterns or trends related to particular commodities. For instance, an increase in positive sentiment towards crude oil may indicate market expectations of a near-term price rise, while negative sentiment towards gold may reflect global economic uncertainty.

By understanding the relationship between social media sentiment and commodity price movements, market participants can make better-informed decisions in their trading strategies [27]. Research endeavors have delved into assessing the impact of social media sentiment on commodity prices, yielding a spectrum of findings. Collis [22] reported a lack of significant impact of social media usage on well-being and academic achievement, implying a potential limitation of its influence on other domains, including commodity prices. Similarly, Sekizawa [28] identified associations, albeit not causality, between consumer confidence and emotion-related variables, indicating that the interplay between social media sentiment and commodity prices might be intricate and indirect. Conversely, Carter [29] showcased the potential for social network spillovers to affect technology adoption and yields, particularly within the realm of agricultural subsidies, suggesting that social media sentiment could indirectly shape commodity prices through such channels. Nevertheless, further research is imperative to elucidate the intricate relationship between social media sentiment and commodity prices.

This research demonstrates that social media sentiment significantly impacts commodity price movements in the market. The sentiment expressed by social media users can reflect market expectations, fears, or perceptions regarding economic conditions and other factors affecting the supply and demand of commodities. Hence, social media sentiment analysis can provide valuable insights to market participants in understanding trends and patterns of behavior that may influence commodity prices. Despite strong evidence of the relationship between social media sentiment and commodity price movements, the research also highlights some complexities in this relationship. Some studies find that the relationship between social media sentiment and commodity prices is not always direct or causal but can involve more complex pathways, such as its influence on consumer confidence or technological behaviors. This suggests the importance of not only analyzing the sentiment itself but also understanding the context and other factors that may influence the relationship between sentiment and commodity prices.

3.2 Patterns or Trends that can be Identified from Social Media Sentiment towards Specific Commodities

Extensive research has been devoted to identifying discernible patterns and trends in social media sentiment pertaining to specific commodities. Studies indicate that emotions conveyed on social media platforms wield a notable influence on returns within commodity markets [30]. Moreover, sentiment analysis applied to social media data has proven effective in forecasting the volatility of cryptocurrencies, achieved through the examination of emotional expressions in tweets concerning particular digital assets [31]. Furthermore, investigations into sentiment surrounding genetically modified organisms (GMOs) across diverse social media platforms have unveiled prevailing negativity towards GMOs among a substantial segment of users [32]. These findings underscore the significance of scrutinizing social media sentiment to gauge public perceptions regarding commodities such as GMOs, cryptocurrencies, and other assets, thereby furnishing investors and market analysts with invaluable insights. The identification of patterns or trends from social media sentiment towards specific commodities is an intriguing subject to investigate within the context of market analysis [33]. Social media has become a primary platform where users share opinions, perspectives, and information regarding various commodities, ranging from energy to agricultural produce [34].

By analyzing sentiment expressed in posts, comments, and discussions on platforms such as Twitter, Facebook, and other online forums, researchers can uncover specific patterns associated with commodity market behavior [35]. For instance, an increase in positive sentiment towards a commodity may indicate the potential for price escalation in the future, while negative sentiment could serve as a signal of price decline or market instability. Understanding these patterns enables market participants to make more informed decisions in risk management and investment decision-making. Research investigating the influence of social media sentiment on particular commodities has produced varied outcomes. Collis [22] concluded that social media usage did not significantly impact well-being and academic success, contrasting with findings by Komatsu [36], who observed the potential for informational content to affect perceptions of disposable plastics. Bogliacino [37] underscored the significance of emotions in molding consumer behavior, with emotions like shame, anger, and distress exhibiting greater efficacy in reducing smoking compared to fear and disgust. Collectively, these studies imply that while social media sentiment may not directly sway consumer behavior, it serves as a conduit for the dissemination of information and emotional signals that can influence attitudes and actions regarding specific commodities.

The findings of this research indicate that social media sentiment can provide valuable insights into identifying patterns and trends related to commodity market behavior. Sentiment analysis enables tracking of how opinions and emotions expressed on social media can influence public perception of specific commodities. In this regard, an increase in positive sentiment towards a commodity may serve as a potential indicator for future price hikes, while negative sentiment could signal price declines or market instability. While the research highlights success in identifying patterns and trends of social media sentiment towards specific commodities, it also reveals diversity in the influence of sentiment on market behavior. Some studies suggest that social media usage does not significantly affect well-being and academic success, while others emphasize the significant role of emotions in shaping consumer behavior. This underscores the complexity of understanding the relationship between social media sentiment and commodity market behavior.

3.3 The Influence of Positive and Negative Sentiments on Social Media on Commodity Price Movements

The sway of positive and negative sentiments expressed on social media platforms can wield a notable influence on movements in commodity prices. Research demonstrates that conducting sentiment analysis on platforms like Twitter and StockTwits across different trading hours enables the prediction of future returns, with the timing of postings and the nature of sentiments expressed exerting varying degrees of influence [38]. Furthermore, social network sentiment emerges as a reliable indicator of commodity futures returns, with investor attention serving as a pivotal driver of market dynamics [23]. Notably, the impact of adverse news on stock prices is discerned to be more pronounced than that of positive news, elucidating an asymmetric response effect that underscores the heightened influence of negative sentiment on financial markets [39]. These findings underscore the significance of integrating sentiment analysis derived from social media platforms when evaluating and prognosticating movements in commodity prices. The influence of positive and negative sentiment on social media towards commodity price movements is a crucial area of study in market research [40]. Sentiments expressed by social media users can significantly impact commodity prices [41]. Positive sentiment, for instance, may reflect market optimism regarding the performance of specific commodities, potentially resulting in increased demand and price hikes. Conversely, negative sentiment may signal market concerns or uncertainties, leading to price declines or heightened volatility.

Through sentiment analysis on social media platforms such as Twitter, Facebook, and other online forums, researchers can identify how these positive and negative sentiments impact commodity market behavior. With a better understanding of the influence of social media sentiment, market participants can take wiser steps in responding to price changes and market trends [42]. Empirical investigations have indicated that both positive and negative sentiments expressed on social media platforms hold the potential to shape movements in commodity prices. Yang [43] observed that mindfulness training could potentially ameliorate the adverse impacts of negative information coverage, thereby influencing market sentiment. Similarly, Gozzi [44] demonstrated that neuropeptides such as oxytocin and vasopressin could modulate brain responses to negative social feedback, potentially influencing market sentiment as well. Nonetheless, Collis & Eggers [22] found no direct association between social media usage and well-being or academic success, suggesting that the interplay between sentiment and commodity prices may involve more intricate dynamics than previously assumed.

The findings suggest that both positive and negative sentiments on social media play a significant role in shaping commodity price movements. Positive sentiment may reflect market optimism regarding the performance of specific commodities, potentially boosting demand and prices. Conversely, negative sentiment can signal market concerns or uncertainty, which may lead to price declines or increased volatility. While these findings provide valuable insights into the influence of positive and negative sentiments on social media on commodity price movements, some studies indicate complexities in this relationship. Some studies highlight that social media usage is not directly related to well-being or academic success, suggesting that the interaction between sentiment and commodity prices may involve dynamics more complex than previously anticipated.

3.4 Variance in the Impact of Social Media Sentiment on Various Types of Commodities: Energy, Metals, and Agricultural Commodities

The influence of social media sentiment on various categories of commodities, encompassing energy, metals, and agricultural products, demonstrates considerable variation according to research outcomes. Studies indicate that sentiment prevailing within social networks serves as a reliable predictor of returns on commodity futures, with distinct search volume indices playing a role in forecasting these returns **[23]**. Furthermore, investigations into the relationship between social media sentiment and the stock market suggest a positive impact on stock market returns, particularly stemming from authenticated users on platforms like Weibo **[24]**. However, within the context of the energy sector, Twitter sentiment has been observed to lack a significant impact on returns and volatility, albeit positively influencing trading volume **[45]**. These findings underscore the nuanced and diverse effects of social media sentiment across different categories of commodities. The variation in the impact of social media sentiment across different types of commodities, such as energy, metals, or agricultural commodities, is an intriguing aspect to investigate in market analysis. Each type of commodity may respond to social media sentiment differently, depending on market characteristics and other influencing factors **[46]**. For instance, in the energy sector, positive social media sentiment associated with adverse weather forecasts may boost oil prices, while the same sentiment towards renewable energy sources such as solar or wind may lead to price declines. In the metals sector, positive social media sentiment regarding the demand from specific industries like infrastructure development may trigger price increases for certain metals like steel or copper **[47]**.

Conversely, in agricultural commodities, negative sentiment related to poor weather conditions or crop yields may lead to price hikes for specific agricultural products such as wheat or soybeans **[48]**. By understanding this variation in the impact of social media sentiment, market participants can devise strategies that align more closely with the characteristics of specific markets and manage risks more effectively **[15]**. Research examining the influence of social media sentiment on various commodities elucidates a multifaceted relationship. While certain studies indicate a positive influence, such as utilizing social networks to disseminate information regarding agricultural subsidies **[29]**, others report no significant impact on well-being or academic success **[22]**. The disparity in these findings underscores the necessity for additional research aimed at comprehending the specific factors contributing to the diverse effects of social media sentiment on different categories of commodities.

The findings indicate that the impact of social media sentiment can vary significantly across different types of commodities. Factors such as market characteristics and other influencing factors can affect how each type of commodity responds to social media sentiment. For example, in the energy sector, positive sentiment related to adverse weather forecasts may drive up oil prices, while the same sentiment towards renewable energy sources such as solar or wind may lead to price declines. In the metals sector, positive sentiment associated with demand from specific industries such as infrastructure development may trigger price increases for certain metals like steel or copper. Conversely, in agricultural commodities, negative sentiment related to adverse weather conditions or poor harvests may result in price hikes for specific agricultural products like wheat or soybeans. While some research indicates a positive impact of social media sentiment on certain types of commodities, there are also findings indicating variation and even the absence of impact on other commodity types. This underscores the complexity of the relationship between social media sentiment and various commodity categories, which may be influenced by different factors in each market.

3.5 Effectiveness of Various Sentiment Analysis Methods in Predicting Commodity Price Movements

Various sentiment analysis methodologies have been explored in the realm of predicting commodity price movements. Research indicates that augmenting sentiment analysis with economic theory and external knowledge sources can enhance predictive capabilities within commodity markets [25]. Moreover, integrating sentiment analysis with machine learning techniques such as random forest, eXtreme gradient boosting, and long short-term memory models has been demonstrated to enhance forecasting accuracy for both foreign exchange rates and commodity prices [49].

Random Forest,

$$l(y) = argmax_c\left(\sum_{n=1}^{N} I_{hn(y)=c}\right) \tag{1}$$

eXtreme Gradient Boosting,

$$l(y) = \sum_{n=1}^{N} l(y_i, \hat{y}_i) \tag{2}$$

Long Short-term Memory Models,

$$y_{k+1} = NN(y_k, y_{k-1}, y_{k-2}, y_{k-3}, \dots) \tag{3}$$

The formulas presented describe key variables within different sentiment analysis methods applied to predict commodity price movements. In the Random Forest model, $l(y)$ represents the predicted class for the target variable y, determined by selecting the class c that maximizes the sum of predictions across N trees, each tree's prediction is indicated b $I_{hn(y)=c}$, where $h_n(y)$ is the prediction from the n-th tree. For eXtreme Gradient Boosting (XGBoost), $l(y)$ represents the overall model loss calculated as the sum of individual losses $l(y_i, \hat{y}_i)$, where y_i and $\hat{y}_i$ are the true and predicted values, respectively, for each data point i across N data points. Lastly, in Long Short-Term Memory (LSTM) models, y_{k+1} denotes the forecasted value for the next time step $k+1$, derived from a neural network function $NN(.)$ that leverages prior observations $y_k, y_{k-1}, y_{k-2}, y_{k-3}$ ... to learn temporal dependencies in the data. These methods collectively enhance the precision of sentiment analysis for predicting changes in commodity prices.

Additionally, incorporating emotional scores, oil prices, and weather data into sentiment analysis models has shown effectiveness in predicting trends in agricultural product prices [50]. Furthermore, sentiment indices derived from news-based economic and consumer-based sentiments have emerged as reliable indicators of potential future price bubbles in strategic metal commodities [51]. Collectively, these findings underscore the importance of employing a diverse array of sentiment analysis methods to effectively predict commodity price movements. The effectiveness of various sentiment analysis methods in predicting commodity price movements has become a primary focus in market research [15]. In efforts to anticipate fluctuations in price and market volatility, researchers have developed and tested various sentiment analysis approaches.

Brimblecombe [52] discovered that a 20% price reduction on healthy food items resulted in a notable increase in their purchase, underscoring the capacity for price alterations to influence consumer behavior. This observation finds support in Sekizawa's [28] identification of an association between consumer confidence and emotion-related variables, implying that sentiment can wield an impact on the economic outlook. Bogliacino's [37] research further underscored the sway of emotions on consumer behavior, with a negative effect diminishing the likelihood of purchasing tobacco products. Additionally, Coibion [53] emphasized the significance of information about future interest rates in shaping household expectations and purchasing decisions. Taken together, these studies suggest that sentiment analysis methods, particularly those incorporating considerations of price fluctuations, consumer confidence, and emotional responses, hold promise in effectively predicting movements in commodity prices.

These findings underscore the importance of utilizing various sentiment analysis methods to effectively predict commodity price movements. Integrating sentiment analysis with machine learning techniques and external knowledge sources can enhance prediction accuracy while incorporating factors such as commodity prices, weather, and economic data can enrich sentiment analysis models and improve prediction precision. The results of this research offer valuable insights into the development of sentiment analysis methodologies in predicting commodity price movements. However, some studies may have methodological or contextual limitations that need to be considered in evaluating their findings.

3.6 Factors within Social Media Sentiment that Exert a Greater Influence on Commodity Price Movements

Social media sentiment emerges as a pivotal determinant in shaping commodity price movements, with several key factors influencing its predictive efficacy. Factors such as the intensity of sentiment, the timing of sentiment expression, and the nature of sentiment (positive or negative) hold substantial significance in forecasting commodity returns. Research suggests that extreme levels of sentiment within social networks possess the capacity to alter trading strategies significantly and impact returns notably **[24]**. Furthermore, emotions such as optimism, fear, and joy extracted from both news sources and social media platforms have been identified as influential factors in determining individual commodity returns, highlighting their role in short-term predictability **[23]**. Additionally, sentiment expressed during various hours of tweeting can exert differential levels of influence on future returns, with positive and negative sentiments exerting distinct effects **[54]**. These findings underscore the critical importance of considering nuanced factors within social media sentiment when analyzing and forecasting commodity price movements. Several specific factors within social media sentiment have a greater influence on commodity price movements in the market. Firstly, the level of interaction and user engagement in discussions about particular commodities can serve as important indicators for predicting price movements. The higher the level of user participation and engagement in conversations about a commodity, the greater the likelihood that the sentiment will influence the market **[55]**. Additionally, consistency in sentiment is also a crucial factor. If sentiment consistently indicates a certain direction toward a commodity, it can create significant market momentum. Another factor is the trust and authority of the users involved in expressing their sentiments. Opinions from individuals or entities perceived to have strong knowledge or influence in a particular industry can have a greater impact on market perception **[56]**.

Furthermore, external contexts such as news events or occurrences related to commodities can also amplify or dampen the influence of social media sentiment on commodity prices **[57]**. By understanding these factors more deeply, market participants can more effectively anticipate and respond to changes in commodity prices influenced by social media sentiment. Research findings indicate that social media usage itself does not notably affect well-being and academic success **[22]**. However, its impact on commodity price movements can be significant, primarily through the dissemination of negative news and emotions. Such dissemination can elevate public uncertainty and disrupt consensus, thus influencing commodity prices **[43]**. This phenomenon is particularly pertinent within the realm of monetary policy communications, where different forms of communication can shape inflation expectations **[58]**. Hence, specific elements within social media sentiment, such as the propagation of negative news and emotions, can exert a substantial influence on commodity price movements.

These findings underscore the importance of considering nuanced factors within social media sentiment when analyzing and predicting commodity price movements. Factors such as the level of interaction, consistency of sentiment, and the authority of users within specific industries can exert significant influence on market perception and commodity price movements. Additionally, external factors such as news events or commodity-related occurrences can further amplify or dampen the impact of social media sentiment. The results of this research provide crucial insights into the specific factors within social media sentiment that affect commodity price movements. However, some studies may have methodological or contextual limitations that need to be considered in evaluating their findings.

3.7 Implications of Findings on the Development of More Accurate Price Prediction Models and Trading Practices in Commodity Markets

The research findings suggest that integrating advanced techniques such as ensemble empirical mode decomposition (EEMD), fractal Hurst index analysis, and long short-term memory neural networks (LSTM) can substantially improve accuracy in predicting commodity prices **[59][60]**. Artificial intelligence-based models, particularly effective in stable economic conditions, demonstrate superior forecasting capabilities over short and medium timeframes, thereby facilitating effective hedging of purchase prices **[61]**. Furthermore, deep learning models have exhibited aptitude in forecasting commodity prices, outperforming traditional models like ARIMA and exponential smoothing **[62]**. However, it is essential to recognize that directly simulating commodity prices using models such as Geometric Brownian Motion may not yield precise results, underscoring the distinct nature of commodity pricing relative to financial assets [63]. These insights have substantial implications for refining price prediction models and crafting trading strategies in commodity markets, thereby enhancing risk management and informing investment decisions.

The studies conducted by Todd [64], Dakin [65], Wang [66], and Coibion [58] underscore the significance of recognizing and mitigating bias across various domains. Todd's examination of demand response programs underscores the imperative of identifying and addressing underlying biases, an approach that holds relevance for refining the accuracy of price-prediction models in commodity markets. Similarly, Dakin's investigation into patient-level simulation models highlights the importance of accounting for diverse forms of uncertainty, a principle that can be extrapolated to trading strategies within commodity markets. Wang's review of methodologies for extrapolating evidence from randomized controlled trials to distinct populations offers potential avenues for enhancing the generalizability of price-prediction models. Lastly, Coibion's research on the impact of monetary policy communications on inflation expectations underscores the role of information dissemination in shaping market behavior, thereby offering insights that can inform trading practices.

The findings of this research indicate that the utilization of advanced techniques in the development of commodity price prediction models can have significant implications for enhancing prediction accuracy and trading strategy effectiveness. Specifically, artificial intelligence and deep learning-based models show promise in outperforming traditional models, enabling market participants to make more informed decisions in risk management and investment. While these findings offer valuable insights into the development of more accurate price prediction models, it is important to bear in mind that each model comes with limitations and assumptions that need careful consideration. Furthermore, integrating these advanced models into trading practices in commodity markets may entail implementation challenges and policy considerations.

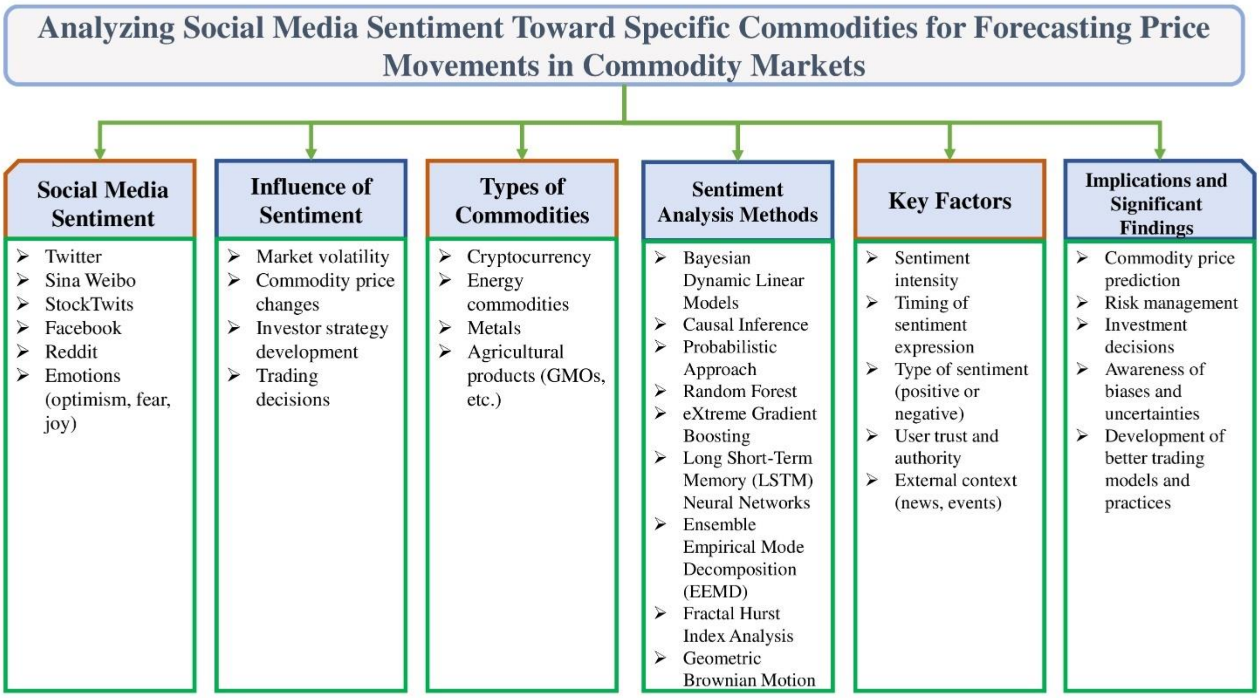

Figure 2. Key Research Findings.

The research landscape surrounding the relationship between social media sentiment and commodity price movements encompasses a multifaceted exploration of various methodologies and factors. Social media sentiment analysis, conducted on platforms such as Twitter, Sina Weibo, and StockTwits, emerges as a pivotal tool for predicting and understanding commodity price fluctuations. Emotions expressed within social networks, including optimism, fear, and joy, play a significant role in shaping investor strategies and market outcomes. The influence of sentiment intensity, timing of expression, and type (positive or negative) on commodity returns highlights the nuanced dynamics within social media sentiment. Moreover, the impact of sentiment varies across different categories of commodities, including cryptocurrencies, energy commodities, metals, and agricultural products, underscoring the need for a tailored approach to analysis and prediction. Various sentiment analysis methods, such as Bayesian Dynamic Linear Models, random forest, eXtreme

Gradient Boosting, and long short-term memory neural networks, offer diverse avenues for predicting commodity price movements with enhanced accuracy. Additionally, understanding key factors such as user trust and authority, as well as external contextual factors like news events, is crucial for interpreting sentiment's influence accurately.

Table 2. Comparison of Sentiment Analysis Methods for Predicting Commodity Price Movements

Sentiment Analysis Methods	Data	Comparison Data Sentiment
Bayesian Dynamic Linear Models	Time series data from social media posts and historical price data	Captures temporal changes in sentiment and accounts for market volatility
Causal Inference	Observational data with external variables (e.g., news, events)	Identifies causal relationships between sentiment shifts and price changes, useful for intervention impact assessment
Probabilistic Approach	Probabilistic sentiment scores from various sources	Manages uncertainty and biases by calculating probability distributions for sentiment, enhancing robustness
Random Forest	Features extracted from social media text, such as sentiment polarity and intensity	Non-linear relationships between sentiment features and price movement, handles large feature sets
eXtreme Gradient Boosting (XGBoost)	Structured data from social media interactions and sentiment features	Boosting technique that reduces overfitting and enhances prediction accuracy in noisy data
Long Short-Term Memory (LSTM) Neural Networks	Sequential data, including historical prices and sentiment trends	Captures long-term dependencies in sentiment, especially useful for continuous time series data
Ensemble Empirical Mode Decomposition (EEMD)	Decomposed social media sentiment and market price series	Separates noise from trend in sentiment data, improving the signal quality for price prediction
Fractal Hurst Index Analysis	Historical price data and sentiment time series	Analyzes the persistence or mean-reverting behavior of sentiment and market movements, useful for trend prediction
Geometric Brownian Motion	Continuous sentiment scores and price variations	Models random sentiment fluctuations, applicable in high-volatility markets but limited in capturing structural changes

Table 2 presents a comparative analysis of various sentiment analysis methods employed for predicting commodity price movements. Each method offers unique strengths in terms of handling data complexity, accuracy, and interpretability. Bayesian Dynamic Linear Models provide a probabilistic approach to analyzing time series data, allowing for flexibility in capturing dynamic sentiment patterns. Random Forest and eXtreme Gradient Boosting (XGBoost) are robust machine learning techniques known for their effectiveness in managing large datasets and identifying key sentiment variables impacting commodity prices. Long Short-Term Memory (LSTM) neural networks excel in sequential data processing, making them suitable for capturing temporal dependencies in sentiment shifts over time. Ensemble Empirical Mode Decomposition (EEMD) and Fractal Hurst Index Analysis contribute to the understanding of sentiment intensity and pattern recognition, enhancing model precision. Additionally, the Geometric Brownian Motion model offers a simulation-based approach, valuable for understanding price fluctuations influenced by sentiment volatility. Collectively, these methods reflect a diverse set of approaches, each contributing to a nuanced understanding of how social media sentiment impacts commodity markets, thus supporting more accurate predictions and informed trading strategies. Addressing biases and uncertainties inherent in sentiment analysis remains imperative, with probabilistic approaches like Probabilistic Deep Learning and Quantile Regression offering promising avenues for quantifying and managing uncertainties effectively. Furthermore, the integration of causal inference models and methodological approaches like the Difference in Different methods enriches the predictive capabilities of sentiment analysis models, particularly in forecasting the impact of intervention programs on commodity price movements.

The collective synthesis of these research endeavors underscores the complexity and dynamism inherent in understanding the relationship between social media sentiment and commodity prices, advocating for interdisciplinary methodologies and rigorous validation frameworks to advance predictive accuracy and inform decision-making processes in commodity markets. The included studies and the review process present several limitations that must be addressed to strengthen the analysis of social media sentiment's impact on commodity prices. First, many studies rely on specific platforms like Twitter or Sina Weibo, which may not capture the full spectrum of sentiment across all social media channels, potentially biasing results toward the demographics of these platforms. Additionally, sentiment analysis methods vary widely in complexity and accuracy; simpler techniques may fail to capture nuanced sentiments, while more advanced models, such as LSTM neural networks and Bayesian Dynamic Linear Models, require extensive data and computational resources, limiting their accessibility. Another limitation lies in the temporal focus of many studies, which often only capture short-term sentiment effects, thus overlooking long-term trends or cyclical market behaviors. The review process itself also carries limitations, as the exclusion of non-English and older publications might have omitted relevant findings from other regions or periods, reducing the generalizability of conclusions. Furthermore, the diversity of methodologies and sample sizes in the selected studies introduces potential inconsistencies, as differing levels of rigor and contextual factors make direct comparisons challenging. Addressing these limitations is essential for enhancing the predictive power and reliability of sentiment-based forecasting models in commodity markets.

4. CONCLUSIONS

Based on the results and discussions, this study concludes that social media sentiment significantly influences commodity price movements, revealing a complex relationship that varies across commodity types, market characteristics, and external contexts, such as regional conditions and economic events that mediate or moderate sentiment's impact on prices. These findings align with the study's objectives by confirming that social media sentiment affects commodity prices, while also identifying specific sentiment factors such as intensity, polarity, and timing that most strongly influence these movements. Utilizing advanced clustering and time series methods, including Geometric Brownian Motion and LSTM neural networks, this study demonstrates that refined models improve prediction accuracy for specific commodities like fuel oil and cryptocurrencies. Moreover, this research addresses the objective of understanding geographical variations in sentiment effects, highlighting that local market sentiments can drive price trends distinct from global patterns. Future research should integrate external factors like news events and global economic conditions to further enhance sentiment analysis applications in forecasting commodity prices.

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