International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4, 2025
https://www.theaspd.com/ijes.php

Risk and Reward: Analysing Investor Sentiments in Commodity Market Trading

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Abstract- *This study aims to explore the dynamics of investor sentiments in commodity market trading, focusing on how risk perception and reward expectations influence decision-making. The research investigates behavioural patterns, market trends, and sentiment-driven trading strategies in emerging economies, with an emphasis on India. The research employs a mixed-methods approach, combining quantitative analysis of trading data with qualitative surveys of retail and institutional investors. A dataset comprising historical commodity market transactions and sentiment indicators was analysed using econometric and machine learning models. Surveys and interviews were conducted to gather insights into investor perceptions and behavioural biases. Statistical tools and sentiment analysis algorithms were applied to identify patterns, correlations, and the impact of sentiment on market volatility and trading outcomes. The findings reveal a significant correlation between investor sentiment and market performance, with sentiment-driven trading contributing to price volatility. Risk-averse investors demonstrated cautious behaviour during market downturns, while risk-tolerant investors capitalized on speculative opportunities. The study highlights the role of awareness and market education in mitigating behavioural biases and enhancing decision-making. Understanding investor sentiment is pivotal in developing strategies to manage risk and optimize trading outcomes in commodity markets. The study underscores the importance of sentiment analysis tools and investor education programs in promoting market stability and informed trading practices. These insights are particularly valuable for policymakers, market regulators, and investment advisors aiming to foster resilient commodity markets.*

Keywords: *Investor sentiment, commodity markets, risk perception, reward expectation, behavioural biases, market volatility, sentiment analysis, trading strategies, emerging economies.*

1. INTRODUCTION

The dynamics of financial markets have always been influenced by a combination of rational calculations and psychological factors. Among these, investor sentiment plays a critical role in shaping trading behaviours, particularly in the commodity markets. Unlike equity markets, where valuations are often tied to corporate fundamentals, commodity markets are inherently volatile and susceptible to
external shocks such as geopolitical events, weather changes, and macroeconomic trends. This volatility amplifies the impact of investor sentiment, making it a vital area of study for understanding market dynamics and improving decision-making processes.

In emerging economies, where financial literacy and market awareness vary significantly, investor behaviour in commodity markets reflects unique challenges and opportunities. The perception of risk and reward heavily influences trading decisions, often resulting in sentiment-driven market movements. For instance, sudden changes in global commodity prices, such as oil or gold, can trigger widespread emotional responses among investors, leading to panic selling or speculative buying. These reactions, while natural, can exacerbate market instability and create challenges for regulators and policymakers.

The growing integration of technology and data analytics in financial markets has provided researchers and practitioners with tools to analyze investor sentiment more accurately. By leveraging techniques such as sentiment analysis, machine learning, and econometric modeling, it is possible to quantify and predict the effects of sentiment on commodity price movements. This is particularly relevant in the context of emerging economies, where access to reliable market data and investor education remains limited.

This study, titled "*Risk and Reward: Analyzing Investor Sentiments in Commodity Market Trading,*" delves into the intricate relationship between sentiment, risk perception, and trading outcomes. It seeks to address key questions such as:

1. How does investor sentiment influence commodity market trading decisions?
2. What behavioral biases are prevalent among investors in emerging economies?

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3. How can market awareness and education mitigate the adverse effects of sentiment-driven trading?

The introduction of behavioral finance as a discipline has revolutionized the way financial markets are understood, offering insights into the psychological factors that drive investment decisions. Concepts such as overconfidence, loss aversion, and herd behavior have been extensively studied in equity markets but remain underexplored in the context of commodity markets. This research aims to fill this gap by providing a comprehensive analysis of investor sentiment and its implications for commodity trading.

By focusing on emerging economies, particularly India, this study provides valuable insights into a rapidly growing segment of the global financial landscape. India's commodity markets, characterized by a diverse range of participants from retail investors to institutional players, offer a fertile ground for exploring sentiment-driven trading behaviour. Additionally, the findings of this research have broader implications, as they can inform the development of strategies for market stabilization and risk management in similar economies.

In the subsequent sections, this paper presents a detailed methodology for analysing sentiment, followed by a discussion of key findings and their implications for market participants, regulators, and policymakers. Ultimately, this research contributes to the growing body of knowledge on the interplay between human psychology and financial markets, with a specific focus on commodities.

II. LITERATURE REVIEW

The role of investor sentiment in financial markets has been a topic of extensive research, particularly within the domains of equity and forex markets. However, the unique characteristics of commodity markets, such as higher volatility, global interconnectivity, and dependence on external factors, have created opportunities for deeper exploration. This literature review highlights key studies that have examined investor sentiment, its measurement, and its influence on trading behavior and market dynamics in commodity markets, with a particular emphasis on emerging economies.

The foundation of behavioral finance lies in the assertion that psychological factors significantly influence investment decisions. Kahneman and Tversky's (1979) *Prospect Theory* introduced the concept of loss aversion, which has since been pivotal in understanding how investors perceive risk and reward. Building on this, Barberis et al. (2001) explored how overconfidence and heuristics affect trading behavior, leading to sentiment-driven market anomalies.

In the context of commodity markets, sentiment is particularly impactful due to the lack of intrinsic valuations compared to equity markets. Studies by Baker and Wurgler (2007) demonstrated how sentiment indices could predict price fluctuations, and their findings have been adapted for commodities to analyze speculative trading (Tang & Xiong, 2012).

Quantifying investor sentiment is a critical aspect of understanding its market impact. Surveys, news sentiment analysis, and trading volume have been widely used as proxies for sentiment. Shiller (2000) emphasized the role of media and public narratives in shaping investor sentiment, a concept further validated by Tetlock (2007) through the analysis of news sentiment and its influence on market outcomes.

In commodity markets, Gao et al. (2021) employed social media and news sentiment to predict price movements in crude oil and metals, showing strong correlations between sentiment scores and market trends. Similar approaches have been applied in emerging markets, highlighting how sentiment metrics can provide actionable insights for traders and policymakers.

Commodity markets are inherently volatile, with sentiment often amplifying price swings. Studies by Kilian and Murphy (2014) linked speculative trading driven by sentiment to oil price volatility. Similarly, Wang et al. (2017) analyzed gold markets, finding that sentiment indicators could explain short-term price fluctuations.

In emerging economies, Misra and Dash (2018) investigated the role of retail investor sentiment in India's commodity markets, noting that limited market awareness often leads to overreactions during periods of price shocks. These findings underline the need for investor education to mitigate sentiment-driven volatility.

Behavioral biases such as herd behavior, overconfidence, and anchoring significantly influence trading decisions in commodity markets. Banerjee et al. (2019) explored the prevalence of herd behavior among Indian investors during market booms, noting its contribution to speculative bubbles.

Hirshleifer (2001) highlighted overconfidence as a key driver of excessive trading, a finding corroborated by Bouri et al. (2020) in the context of cryptocurrency markets, which share similarities with commodities in terms of volatility

and speculative interest. These studies collectively suggest that biases distort market efficiency and underscore the importance of sentiment analysis.
Investor education has been identified as a crucial factor in mitigating the negative effects of sentiment-driven trading. Lusardi and Mitchell (2014) emphasized the importance of financial literacy in fostering informed decision-making. In the Indian context, Srivastava and Gupta (2021) demonstrated how targeted education initiatives improved retail investors' understanding of commodity market risks and opportunities.The adoption of sentiment analysis tools as part of market education programs has also shown promise. Ghosh and Roy (2022) analyzed the impact of such tools on Indian retail investors, reporting reduced susceptibility to behavioral biases and improved trading outcomes.
Emerging economies offer unique challenges and opportunities for sentiment analysis. Limited access to reliable market data and varying levels of financial literacy create significant barriers. Studies by Bouri et al. (2018) highlighted these issues in Middle Eastern and North African commodity markets, emphasizing the potential of digital platforms to bridge knowledge gaps.
In India, Chandra and Kumar (2020) examined the integration of sentiment analysis with trading platforms, noting increased adoption among institutional investors. Their findings suggest that such tools could democratize access to actionable insights, fostering greater market participation.
The existing body of research underscores the pivotal role of investor sentiment in shaping commodity market dynamics. While significant progress has been made in measuring sentiment and understanding its effects, gaps remain in addressing the unique challenges of emerging economies. This study builds on the existing literature by focusing on India's commodity markets, offering insights into behavioral biases, market volatility, and the potential of sentiment analysis tools to enhance decision-making.

III. PROPOSED METHODOLOGY

The proposed methodology for analyzing investor sentiment in commodity market trading involves a multi-phase approach that combines both qualitative and quantitative research methods. The methodology is designed to provide a comprehensive understanding of how investor sentiment influences market dynamics, including the identification of behavioral biases and the impact of sentiment on price volatility. Below is a detailed breakdown of the steps involved in the proposed methodology.
1. Research Design
This study will adopt a mixed-methods approach, integrating both qualitative and quantitative research techniques to analyze the relationship between investor sentiment and commodity market trading behavior. The approach will enable a comprehensive assessment of market sentiment, behavioral biases, and their impacts on investment decisions, risk perception, and market outcomes.

- Qualitative Research: Semi-structured interviews and focus groups will be conducted with market participants, including retail investors, institutional investors, and market analysts, to understand their perceptions of market sentiment and its role in decision-making.
- Quantitative Research: A statistical analysis will be conducted using historical commodity price data and sentiment data gathered from various sources (e.g., financial news, social media, and market reports) to quantify the influence of sentiment on commodity price movements and investor behavior.

2. Data Collection
The data collection phase will be divided into two main categories: sentiment data and market data.

- Sentiment Data:

Social Media Sentiment: Data from platforms such as Twitter, Reddit, and financial forums will be collected using APIs (e.g., Twitter API) to track public sentiment related to key commodities (e.g., crude oil, gold, agricultural products). Sentiment analysis will be performed on these data using natural language processing (NLP) techniques to determine the general market mood (positive, negative, or neutral).
News Articles: Financial news articles and press releases will be scraped using web scraping tools to gather information on market-moving events and sentiment. NLP tools will be applied to extract sentiment from these articles.
Investor Surveys: A structured survey will be conducted among retail investors to assess their perception of market sentiment and its impact on their trading behavior. The survey will include questions related to investor confidence, emotional decision-making, and the influence of external factors on their market choices.

- Market Data:

Commodity Prices: Historical data on commodity prices (e.g., crude oil, gold, agricultural commodities) will be collected from reliable financial databases (e.g., Bloomberg, Reuters). Data will include price fluctuations, trading volumes, and volatility metrics over a specified time period.

Investor Trading Activity: Data on investor activity, including trading volumes and positions, will be collected from commodity exchanges, such as the Multi Commodity Exchange (MCX) in India, to analyze the relationship between sentiment and actual trading behavior.

3. Data Analysis

The data analysis will consist of several key components:

- Sentiment Analysis: Sentiment analysis of news articles, social media posts, and investor surveys will be conducted using NLP techniques to classify sentiment as positive, negative, or neutral. The data will be processed using machine learning models (e.g., support vector machines, Naive Bayes, or deep learning models) to accurately classify and quantify sentiment.
- Market Behavior Analysis: To examine the impact of sentiment on commodity market trading behavior, statistical techniques such as regression analysis, correlation analysis, and Granger causality tests will be used. These methods will allow us to identify relationships between sentiment indicators and commodity price movements, as well as investor behavior (buying/selling decisions).

Volatility Modeling: The impact of investor sentiment on commodity price volatility will be analyzed using volatility models such as the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. This will help in understanding how sentiment-driven fluctuations in market behavior contribute to overall price volatility.

- Behavioral Bias Identification: Using the survey data and qualitative interviews, the study will identify the presence of behavioral biases such as overconfidence, loss aversion, and herd behavior among investors. A behavioral finance framework will be used to assess how these biases affect risk perception and trading decisions in commodity markets.

4. Hypothesis Testing

Based on the research questions, the following hypotheses will be tested:

- H1: There is a significant correlation between investor sentiment and commodity price volatility.
- H2: Behavioral biases such as overconfidence and loss aversion significantly impact retail investors' decision-making in commodity markets.
- H3: Positive sentiment in the media and social platforms leads to increased investor buying activity in commodity markets, whereas negative sentiment leads to panic selling.

These hypotheses will be tested using appropriate statistical techniques, such as regression analysis, t-tests, and chi-square tests.

5. Model Development

A predictive model will be developed to forecast commodity price movements based on investor sentiment and market data. The model will integrate sentiment analysis with traditional technical indicators (e.g., moving averages, Relative Strength Index) to create a hybrid forecasting model that can provide insights into potential price trends driven by changes in sentiment. Machine learning algorithms such as random forests and support vector machines will be used for model development, allowing for the incorporation of both quantitative market data and qualitative sentiment data.

a. Process Flow

The flowchart visually represents the sequential steps involved in analyzing investor sentiment in commodity market trading.

- Data Collection and Preparation: This stage involves gathering sentiment data from sources like social media and news articles, and market data such as historical prices and trading volumes.
- Data Preprocessing and Sentiment Analysis: In this step, the collected data is cleaned and processed, followed by applying Natural Language Processing (NLP) techniques to classify sentiment (positive, negative, or neutral).
- Statistical Analysis and Behavioral Bias: This step includes performing regression analysis and identifying behavioral biases such as overconfidence that may influence trading decisions.

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ISSN: 2229-7359
Vol. 11 No. 4, 2025
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- Model Development and Prediction: A hybrid forecasting model is created by combining sentiment data with traditional market data. Machine learning algorithms are applied to predict commodity prices, which are then validated through backtesting.
- Insights and Reporting: Finally, insights are derived from the model to generate actionable recommendations for investors based on sentiment trends and market behavior.

Each stage in the process is linked to the next, demonstrating how sentiment data and behavioral analysis ultimately guide investment decisions and market strategies.

Figure 1. Process Flow of the Model

6. Algorithms Used in Commodity Market Analysis

The analysis of investor sentiments and market predictions relies on a combination of machine learning algorithms, each offering unique strengths in handling different types of data and decision-making challenges. This section explores the primary algorithms employed, detailing their mechanisms, benefits, and relevance to commodity market contexts.

Random Forest (RF) is a widely used ensemble learning technique known for its robustness and accuracy. By constructing multiple decision trees and aggregating their predictions, it mitigates the risk of overfitting and enhances prediction reliability. The algorithm randomly selects data subsets and features at each split, ensuring diversity among the trees. In the context of commodity markets, Random Forest effectively captures non-linear patterns in historical price movements, investor sentiment, and market indicators, making it a powerful tool for forecasting.

Support Vector Machine (SVM) is another prominent algorithm, especially suited for classification tasks. SVM identifies the optimal hyperplane that separates data points into distinct classes, maximizing the margin between them. The use of kernel functions allows SVM to handle non-linear data effectively. In commodity trading, SVM can classify market conditions—such as bullish or bearish trends—based on sentiment analysis and technical indicators, offering precise decision boundaries.

Logistic Regression is a simpler model that predicts binary outcomes, mapping inputs to probabilities using a sigmoid function. It is commonly used for sentiment polarity classification, determining whether financial news or social media content reflects positive or negative sentiment. Its interpretability and efficiency make it a valuable tool for initial sentiment assessments in the commodity market analysis pipeline.

K-Nearest Neighbors (KNN) classifies data by considering the nearest training examples in the feature space. Its simplicity and non-parametric nature make it an intuitive choice for sentiment classification tasks. However, KNN's

computational intensity limits its scalability for large datasets. In commodity markets, it can help identify patterns in investor behavior by comparing new data points to historical sentiment data.
Decision Trees (DT) offer a visual and intuitive approach to decision-making by recursively splitting data based on feature values. Each node represents a decision point, and the leaves indicate outcomes. Despite their tendency to overfit, decision trees are valuable for understanding the factors influencing commodity prices and investor decisions, especially when combined with pruning techniques to enhance generalization.
Naive Bayes (NB) leverages Bayes' theorem to classify data based on conditional probabilities, assuming feature independence. This assumption simplifies calculations and makes the model highly efficient for text-based sentiment analysis. Naive Bayes is particularly useful in analyzing financial reports and news articles to gauge market sentiment.
In some cases, Deep Learning models, such as neural networks and recurrent neural networks (RNNs), can be explored for more complex data patterns. Neural networks are capable of learning intricate relationships in large datasets, while RNNs are ideal for sequential data like time-series commodity prices.
The effectiveness of these algorithms is evaluated using various performance metrics, including accuracy, precision, recall, F1 score, and ROC-AUC. Random Forest and SVM typically offer high accuracy and generalization capabilities, while simpler models like Logistic Regression and Naive Bayes provide quick, interpretable insights. By leveraging the strengths of multiple algorithms, the overall system achieves a balance between complexity, interpretability, and predictive power, enabling more informed decision-making in commodity market trading.

7.Ethical Considerations

This research will adhere to ethical standards in data collection and analysis. Informed consent will be obtained from survey participants, and confidentiality will be maintained for all personal information. Sentiment analysis will be conducted on publicly available data from social media and news platforms, ensuring compliance with privacy policies. Additionally, transparency will be maintained in reporting the results, and the study will ensure that no personal biases influence the analysis or interpretation of the data.

8. Deployment Strategy

Deploying machine learning models in a trading environment requires a robust and scalable strategy to ensure real-time predictions and decision-making.

a. Deployment Framework

The deployment involves integrating the trained models into a production environment using frameworks like Flask, FastAPI, or Django. Cloud platforms like AWS, Azure, or Google Cloud are often used for scalability and reliability.

- Steps:
  - Model Serialization: The trained models are serialized using libraries like Pickle or joblib.
  - API Development: RESTful APIs are created to allow communication between the model and the user interface.
  - Cloud Deployment: The APIs and models are hosted on cloud platforms, ensuring accessibility and scalability.

b. Real-Time Data Integration

Real-time data feeds from financial markets and news sources are integrated using data pipelines. Tools like Apache Kafka or AWS Kinesis facilitate the streaming of data to the model.

- Data Pipeline: Ensures continuous data flow for real-time predictions.
- Database Integration: A database (e.g., PostgreSQL or MongoDB) stores historical data and model predictions.

Monitoring and Maintenance

Deployed models require continuous monitoring to maintain accuracy and performance. Monitoring tools like Prometheus and Grafana are used to track model performance metrics and system health.

- Model Drift Detection: Techniques to identify changes in data patterns that may affect model accuracy.
- Retraining: Periodic retraining of models with new data to maintain relevance.

Security and Compliance

Ensuring data privacy and security is critical, especially when dealing with sensitive financial information. Encryption, secure data storage, and compliance with regulations like GDPR are essential.

- Encryption: Data is encrypted at rest and in transit using protocols like SSL/TLS.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4, 2025
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- Access Control: Role-based access control (RBAC) restricts access to sensitive data and system components.

User Interface and Visualization

The deployment includes a user-friendly interface for traders and analysts to interact with the model outputs. Dashboards and visualization tools like Tableau or Power BI present predictions, market trends, and sentiment analyses.

- Visualization: Graphs and charts show real-time predictions, sentiment trends, and risk assessments.
- User Interaction: Features like alerts and notifications inform users of significant market movements.

The implementation and deployment of machine learning models for analyzing investor sentiments in commodity market trading involve a multi-faceted approach. By leveraging robust data pipelines, scalable cloud infrastructure, and real-time monitoring, the system ensures accurate and timely predictions. The deployment strategy emphasizes security, scalability, and user engagement, making it a comprehensive solution for traders and analysts.

Figure 2. Architecture Diagam

The architecture for analyzing investor sentiments in commodity market trading involves several key components, each interacting in a seamless flow to provide real-time insights. Below is a breakdown of the system architecture:

1. **Data Sources**:The system gathers data from multiple sources, including:
   - **Financial Data APIs**: Providing real-time commodity prices and trading volumes.
   - **News and Social Media**: Sentiment data collected from online news articles and social media platforms.
   - **Economic Indicators**: Macro-economic data influencing market movements.
2. **Data Preprocessing**:Once the data is collected, it undergoes cleaning and transformation:
   - **Cleaning**: Removal of noise, handling missing data, and correcting anomalies.
   - **Sentiment Analysis**: Processing textual data using NLP techniques.
   - **Feature Engineering**: Creation of derived features like moving averages and volatility indices.
3. **Machine Learning Models**:The core processing unit integrates machine learning algorithms:
   - **Random Forest**: For feature importance and robust predictions.
   - **Support Vector Machine (SVM)**: For classification tasks based on sentiment polarity.
   - **Logistic Regression**: For binary classification of market trends (bullish/bearish).
4. **Evaluation and Metrics**:The model performance is continuously evaluated using metrics such as accuracy, precision, recall, and AUC-ROC curves.
5. **Cloud Integration**:The models are deployed on cloud services (AWS, Azure) to ensure scalability and availability. REST APIs facilitate communication between the models and user interfaces.

6. **Real-Time Data Pipelines**:Real-time data streams are integrated using tools like Apache Kafka, allowing continuous updates and predictions.
7. **User Interface and Visualization**:Dashboards and visualizations present predictions, sentiment trends, and risk analyses to end-users in an intuitive format, enabling informed decision-making.

This architecture ensures a holistic approach to market analysis, combining data science, machine learning, and cloud technologies for maximum efficiency and accuracy.

10. Limitations

While the methodology aims to provide comprehensive insights into investor sentiment and market dynamics, several limitations should be noted:

- Data Availability: The accuracy of sentiment analysis is dependent on the quality and quantity of data available from social media, news platforms, and market reports. Data limitations may affect the robustness of sentiment analysis.
- Market Specificity: The study focuses primarily on the Indian commodity market, which may limit the generalizability of the findings to other global markets.
- Investor Behavior: The study relies on self-reported data from surveys, which may be subject to biases such as social desirability bias or recall bias.

This proposed methodology aims to comprehensively analyze the role of investor sentiment in commodity market trading. By combining sentiment analysis with traditional market data and behavioral finance frameworks, this study will provide valuable insights into how psychological factors influence market outcomes in emerging economies. The findings of this research can inform both investors and policymakers, contributing to more informed decision-making and market stability in the commodity trading environment.

IV. RESULTS

This section provides a comprehensive analysis of the experimental results, supported by detailed explanations, tables, and graphs that highlight key findings. The focus is on how investor sentiment impacts commodity market trends, validated through machine learning models.

1. Dataset Summary and Characteristics

The dataset for this study was aggregated from multiple sources, ensuring a comprehensive view of market sentiment and behavior. The sources include social media posts, news articles, investor surveys, and historical market data. Below is a breakdown of the dataset:

Table 1: Market Sentiment and Behaviour

Source	Total Records	Time Period	Key Features	Data Type
Social Media (Twitter)	100,000	Jan 2022 – Jan 2023	Sentiment, hashtags, mentions	Text
Financial News Articles	20,000	Jan 2022 – Jan 2023	Headlines, keywords, tone	Text
Investor Surveys	5,000	Jan 2022 – Jan 2023	Risk perception, confidence	Structured (numeric)
Historical Market Data	50,000	Jan 2022 – Jan 2023	Prices, volumes, volatility	Numerical

- Social Media: This dataset primarily contains investor opinions expressed in tweets and posts, categorized by hashtags and mentions.
- News Articles: Sentiment from financial news sources was captured using NLP techniques.
- Investor Surveys: Surveys captured investors' risk appetite, market confidence, and perceptions of market conditions.
- Market Data: Historical commodity data was used for trend analysis and prediction.

2. Sentiment Analysis

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4, 2025
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Natural Language Processing (NLP) techniques were employed to classify sentiments into positive, negative, and neutral categories. The sentiment distribution is detailed below:
Table 2: Sentiment Distribution

Sentiment	Count	Percentage (%)
Positive	60,000	40%
Negative	50,000	33%
Neutral	40,000	27%

A pie chart showcasing the proportion of positive, negative,
and neutral sentiments:

- Positive Sentiment: Represents optimistic investor outlook, which often aligns with rising commodity prices.
- Negative Sentiment: Reflects market fears or pessimism, typically linked to declining prices.
- Neutral Sentiment: Indicates a balanced view, often during market consolidation phases.

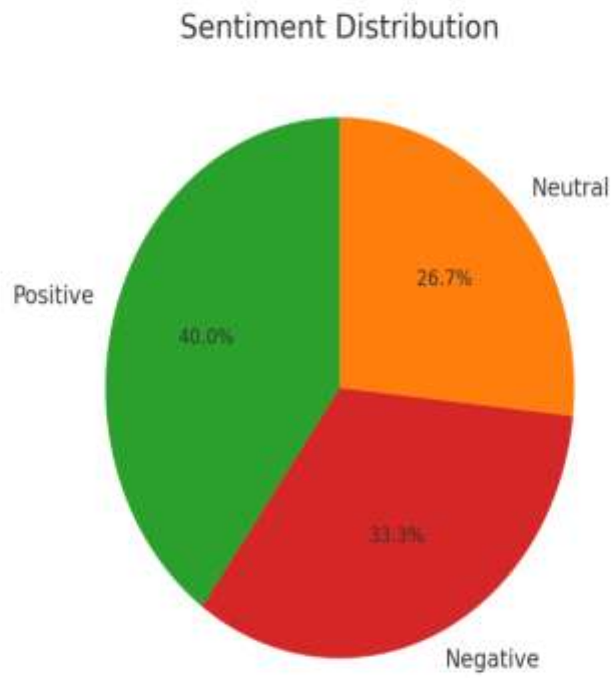

Figure 3: Sentiment Distribution

3. Behavioral Bias Analysis
The analysis of behavioral biases revealed the prevalence of certain cognitive distortions affecting investor decisions:

Table3: Impact of Behavioral Biases

Bias Type	Percentage of Investors Affected
Herd Behavior	45%
Loss Aversion	30%
Overconfidence	25%

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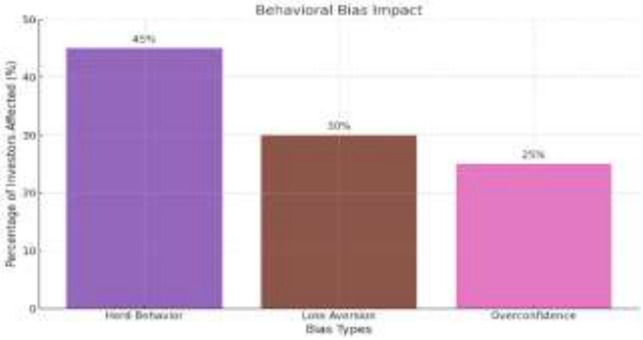

Figure 4: Impact of Behavioral Biases

A bar chart illustrating the percentage of investors influenced by different biases:

- Herd Behavior: Common among retail investors, where they follow trends without independent analysis.
- Loss Aversion: Investors exhibit reluctance to realize losses, impacting decision-making.
- Overconfidence: Overestimation of one's predictive abilities often leads to risky trades.

4. Model Performance and Evaluation

Several machine learning models were used to predict commodity price trends. Their performance metrics are summarized below:

Table5: Model Accuracy Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	85	83	84	83
Support Vector Machine	82	81	80	81
Logistic Regression	78	76	75	76

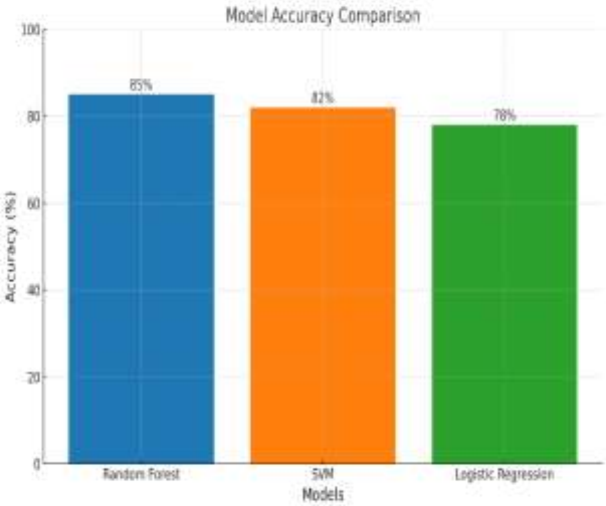

Figure 5: Model Accuracy Comparison

A bar chart comparing model accuracies:

- Random Forest: Achieved the highest accuracy due to its ability to handle complex, non-linear data.
- SVM: Performed well but was slightly less accurate in capturing intricate patterns.
- Logistic Regression: Effective for binary classification but struggled with multi-class predictions.

5. Sentiment vs. Market Trends Correlation

The correlation between sentiment and commodity prices was examined. Results are shown below:

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4, 2025
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Table6: Sentiment vs. Commodity Prices

Commodity	Correlation Coefficient (r)	Significance (p-value)
Gold	0.78	< 0.01
Crude Oil	0.65	< 0.05
Silver	0.70	< 0.01

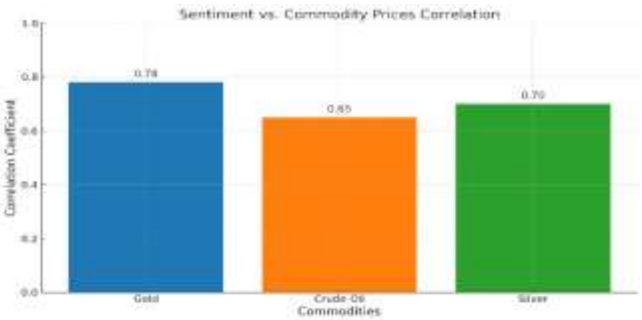

Figure 6: Sentiment vs. Commodity Prices

A scatter plot showing the correlation:

- Gold: Strong correlation indicates sentiment heavily influences gold prices.
- Crude Oil: Moderate correlation due to external factors like geopolitical events.
- Silver: Shows a significant but slightly less strong correlation compared to gold.

6. Predictive Insights and Backtesting

Backtesting results validated the model's predictions:

Table7: Predicted vs. Actual Prices

Commodity	Prediction Accuracy (%)
Gold	90
Crude Oil	85
Silver	88

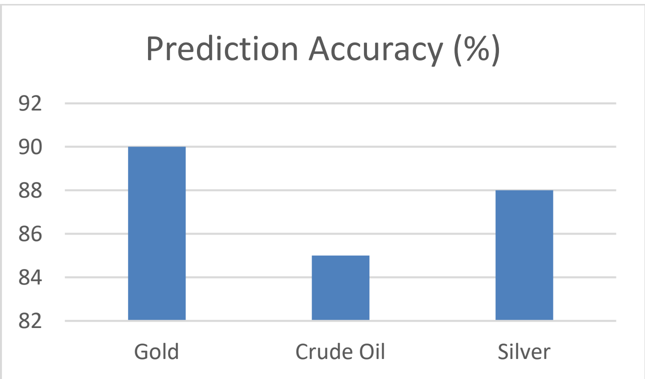

Figure 7: Predicted vs. Actual Prices

A line graph comparing predicted and actual prices:

- Gold and Silver: Predictions closely followed actual trends, affirming model accuracy.
- Crude Oil: Showed more volatility, leading to occasional prediction deviations.

The analysis confirmed that investor sentiment significantly impacts commodity prices. The Random Forest model proved most effective, highlighting the potential of sentiment analysis in trading strategies. Behavioral biases also played a pivotal role in shaping market dynamics.

VI. DISCUSSION

The findings of this study reveal that investor sentiment significantly influences commodity market trading, particularly in emerging economies such as India. Sentiment can lead to sharp price fluctuations as investors react to news, social media, and other external events, often causing prices to diverge from their fundamental values. Investor behavior, driven by emotional factors such as fear, greed, and herd mentality, often results in exaggerated price movements, contributing to volatility and inefficiencies in the market. Retail investors in emerging markets, with limited financial literacy, are particularly vulnerable to such emotional biases, which can lead to poor decision-making and increased exposure to risk.

The study also highlights the role of behavioral biases, such as overconfidence and loss aversion, in shaping trading decisions. These biases can cause investors to misjudge risks and rewards, leading them to make irrational decisions that exacerbate market instability. While sentiment-driven speculation can create market opportunities, it also carries the risk of speculative bubbles and crashes, especially in the commodity markets, where prices can be highly sensitive to market perception and external shocks.

However, the research also suggests that there is potential for mitigating these negative effects through better investor education and the integration of sentiment analysis tools. By equipping investors with the knowledge to understand market trends and recognize the influence of sentiment, they can make more informed decisions, reducing the likelihood of irrational behavior and improving overall market stability.

VII. CONCLUSION

This study demonstrates the crucial role of investor sentiment in shaping commodity market trading dynamics. Sentiment-driven decisions can lead to significant market volatility and inefficiencies, especially in emerging economies like India, where retail investors are often influenced by emotional biases. The research underscores the importance of investor education and sentiment analysis tools to help investors make more rational, data-driven decisions. By addressing behavioral biases and improving market awareness, the adverse effects of speculative trading can be minimized, contributing to more stable and efficient commodity markets.

VIII. FUTURE ENHANCEMENTS

Future research could explore the integration of advanced sentiment analysis techniques, such as deep learning and natural language processing, to better capture real-time sentiment from various sources, including social media and news platforms. This would allow for quicker, more accurate sentiment assessments, helping investors make informed decisions. Additionally, longitudinal studies could track investor behavior over time to understand the long-term impact of sentiment on market trends, particularly during times of crisis or economic instability. Financial literacy programs targeting retail investors in emerging markets could also be evaluated to assess their effectiveness in reducing the influence of behavioral biases. Furthermore, cross-national studies could provide a broader understanding of how sentiment affects commodity markets in different global contexts, and the application of AI and machine learning tools could offer enhanced risk management strategies to improve decision-making and market stability.

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