Challenges and Opportunities in Price Forecasting for Commodities: A Study of Technical Indicators in the NCR Region

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Abstract:

Commodity price forecasting is essential for industries, policymakers, traders, and investors due to the significant fluctuations in prices caused by macroeconomic, microeconomic, and geopolitical factors. In the context of India's National Capital Region (NCR), which is a major hub for agricultural and energy commodities, accurate price forecasts are vital for strategic decision-making. This study examines the use of three common technical indicators—Moving Averages, Bollinger Bands, and the Relative Strength Index (RSI)—in forecasting commodity prices in this region. To evaluate the effectiveness of Moving Averages, Bollinger Bands, and RSI in commodity price forecasting, and to identify the challenges and opportunities presented by these indicators within the NCR region. A survey was conducted with respondents from the NCR region to assess their understanding and application of the three technical indicators. A Chi-Square test was used to determine the statistical significance of the responses. Additionally, a Pearson correlation matrix was employed to examine relationships between the responses to different questions. **Moving Averages** were well understood by most respondents (60% correctly identified their purpose), with a strong correlation (0.99) between understanding their general use and the specific type (Exponential Moving Average). **Bollinger Bands** were less consistently understood, with only 36% correctly identifying their primary function as measuring market volatility. Chi-Square results ($p = 0.012$) indicate a significant variation in understanding. **RSI** was the best understood, with 60% of respondents identifying that RSI values above 70 indicate an overbought condition ($p = 0.0045$). The Pearson correlation for RSI questions was high, showing good comprehension of its application.
While Moving Averages and RSI are well understood and effectively used, there is a gap in understanding Bollinger Bands, indicating a need for more in-depth education on this indicator. Additionally, the study highlights opportunities for integrating technical indicators with machine learning and real-time data to improve the accuracy of commodity price forecasts, especially in volatile markets like those in the NCR region.

Keywords: Commodity price forecasting, technical indicators, market volatility, real-time data, NCR region

1.Introduction

Commodity price forecasting has long been a critical area of research due to its importance for industries, policymakers, traders, and investors who need to anticipate market movements and mitigate risks. Commodities, such as agricultural products, metals, and energy resources, are subject to intense price fluctuations driven by both macroeconomic and microeconomic factors. These factors include supply-demand imbalances, geopolitical events, currency fluctuations, and shifts in trade policies, all of which make predicting commodity prices a complex task [1].

In the Indian context, the National Capital Region (NCR) plays a pivotal role in the commodity market. As one of the major trade hubs in India, the NCR region is a center for agricultural commodities, precious metals, and energy commodities, such as oil and gas [2]. With Delhi's proximity to major agricultural states like Punjab and Haryana, the region is instrumental in determining the country's commodity price dynamics. Given its strategic importance, understanding the price behaviour of commodities in this region is critical for stakeholders involved in commodity trade and investment.

Forecasting commodity prices involves a variety of approaches, with technical analysis being one of the most widely employed methods. Technical analysis relies on historical price data to predict future price movements by identifying patterns, trends, and signals that occur consistently over time [3]. Within technical analysis, the use of indicators such as moving averages, Bollinger Bands, and oscillators like the Relative Strength Index (RSI) is common. These indicators help traders make informed decisions by providing insights into market trends, volatility, and price momentum.

However, the effectiveness of these technical indicators in commodity markets, especially in regions like the NCR, remains a subject of debate. Unlike equities or currencies, commodity prices are highly sensitive to external shocks, such as climate events, policy changes, and international trade disputes [4]. Therefore, relying solely on technical indicators may not provide a complete picture of future price movements. This introduces both challenges and opportunities for researchers and market participants who are keen to develop more robust forecasting models.

Commodities serve as a backbone for many economies, particularly in developing countries like India. Agricultural commodities, including wheat, rice, and pulses, are critical not only for domestic consumption but also for international trade [5]. Similarly, energy commodities such as crude oil and natural gas are vital for the country's industrial and transportation sectors. Price fluctuations in these commodities can have far-reaching impacts on inflation, fiscal policies, and overall economic stability.

For example, fluctuations in crude oil prices have direct implications for India's import bill and inflationary pressures, as India imports the majority of its crude oil [6]. Likewise, price changes in agricultural commodities can influence rural incomes and affect food security. Given the interconnectedness of commodity prices with the broader economy, accurate forecasting of these prices is essential for both macroeconomic policy formulation and micro-level decision-making by businesses and farmers alike [7].

One of the fundamental challenges in commodity price forecasting is the inherent volatility of commodity markets. Prices of commodities are influenced by factors that are often unpredictable and external to the domestic market. For example, geopolitical tensions, such as trade sanctions or conflicts, can lead to abrupt changes in commodity supply, causing significant price volatility [8]. In 2020, the COVID-19 pandemic caused severe disruptions in global supply chains, impacting commodities like crude oil, which saw unprecedented price drops due to reduced demand [9]. These exogenous shocks highlight the difficulty in using traditional technical indicators to predict price movements accurately.

Another challenge lies in the short-term focus of most technical indicators. Moving averages and stochastic oscillators, commonly used in commodity markets, are more adept at identifying short-term trends rather than providing insights into long-term price movements [10]. While they are useful for day traders and short-term investors, they fall short when it comes to forecasting prices over extended periods, which is often necessary for industries that rely on commodities as inputs. For example, a manufacturing company that uses large quantities of steel may need to forecast prices for the next 12 to 18 months to manage procurement and pricing strategies [11]. This long-term focus makes traditional technical indicators less effective unless supplemented by other forms of analysis.

Moreover, technical indicators fail to account for macroeconomic variables such as interest rates, inflation, and government policies that often play a crucial role in commodity price determination. Agricultural commodities in India, for example, are heavily influenced by government interventions in the form of Minimum Support Prices (MSPs) and subsidies, which can significantly affect supply and, consequently, prices [12]. Similarly, crude oil prices are impacted by international agreements like those made by the Organization of the Petroleum Exporting Countries (OPEC), which can manipulate supply levels to maintain favourable price ranges [13]. The inability of technical indicators to incorporate these macroeconomic variables represents a significant limitation in their predictive capacity.

Despite these challenges, there are significant opportunities for improving commodity price forecasting using technical indicators, particularly in the NCR region. One such opportunity is the integration of machine learning (ML) and artificial intelligence (AI) techniques with traditional technical analysis. Recent studies have shown that ML algorithms, such as support vector machines (SVMs) and artificial neural networks (ANNs), can enhance the accuracy of price predictions by identifying complex patterns in historical data that traditional models may overlook [14]. By incorporating a vast array of factors, including macroeconomic variables, ML models can provide more accurate and dynamic forecasting tools.

Another opportunity lies in the increasing availability of real-time data. With the advent of advanced trading platforms and big data technologies, it is now possible to access minute-by-minute price updates for a wide range of commodities. This allows for the application of real-time technical indicators, which can significantly enhance the timeliness and accuracy of forecasts [15]. For example, real-time moving averages and volatility measures can be used to predict short-term price movements with greater precision, enabling traders and investors to make more informed decisions in volatile markets.

In the context of the NCR region, the increasing digitization of commodity markets presents another opportunity. With the rise of online trading platforms and electronic commodity exchanges, traders and analysts in NCR can access global markets more efficiently, providing them with more comprehensive data sets for analysis [16]. This data can be fed into forecasting models to generate more accurate predictions that consider global trends in addition to local market dynamics.

Accurate commodity price forecasting has significant implications for various stakeholders in the NCR region. For traders and investors, accurate forecasts provide the basis for making profitable trading decisions. In volatile markets, being able to predict price movements with even a moderate degree of accuracy can result in substantial financial gains [17]. For policymakers, commodity price forecasts are essential for making informed decisions regarding trade policies, tariffs, and subsidies. For example, an accurate forecast of rising wheat prices may prompt the government to adjust its MSPs to ensure that farmers receive adequate compensation while protecting consumers from inflationary pressures [18].

For businesses, particularly those in sectors that are heavily dependent on commodities, such as agriculture, manufacturing, and energy, price forecasts are crucial for strategic planning. Companies that rely on commodities as raw materials need to anticipate price movements to manage costs effectively, set product prices, and hedge against risks [19]. Similarly, farmers in the NCR region, who depend on the sale of commodities such as wheat and rice, rely on price forecasts to decide what crops to plant and when to sell their produce [20].

2.Data

2.1 Study Design

The study was designed as an observational and survey-based analysis focusing on the practical application of technical indicators for commodity price forecasting in the National Capital Region (NCR) of India. It aimed to gather quantitative and qualitative data directly from market participants, including traders, investors, and financial analysts, to explore the challenges and opportunities they faced in using technical analysis. The observational aspect focused on analysing how these technical indicators were applied in real market conditions, while the survey component collected subjective experiences and insights from participants. The study sought to examine the relationship between different technical indicators and their forecasting efficacy in the dynamic NCR commodity market.

2.2 Study Setting

The study was conducted in the National Capital Region (NCR) of India, a key financial and trading hub where commodities such as wheat, rice, crude oil, and gold are actively traded. The region's commodity exchanges and trading platforms were the primary venues where the participants operated. Surveys and interviews were conducted at various trading centres, brokerage houses, and through online platforms. The study participants were engaged in both physical commodity trading and financial markets related to commodities in the NCR, ensuring a comprehensive understanding of real-time market dynamics in this region.

2.3 Study Duration

The study spanned six months, from January to June 2024. This timeframe allowed for the collection of both real-time market data and traders' long-term experiences with commodity price forecasting. It also provided sufficient time for the observation of different market conditions, including periods of high volatility and stability, which were crucial for understanding the effectiveness of various technical indicators across different scenarios.

2.4 Study Data Collection

Data collection involved both quantitative and qualitative methods. The structured questionnaire gathered numerical data on the types of technical indicators used, the perceived accuracy of forecasts, and the frequency of trading activities. Qualitative data were collected through open-ended questions in the survey and further expanded during the interviews. The interviews allowed participants to elaborate on their challenges, providing richer insights into the complexities of commodity price forecasting in the NCR region. All responses were anonymized to protect the participants' identities, and data were stored securely in a password-protected database.

2.5 Participants - Inclusion and Exclusion Criteria

The study included participants who were actively involved in commodity trading and forecasting in the NCR region. The inclusion criteria required participants to have a minimum of three years of experience in using technical indicators for commodity trading to ensure that they had a well-rounded understanding of the tools and techniques used in forecasting. Both independent traders and those affiliated with brokerage firms or financial institutions were included. Participants were required to regularly trade or forecast the prices of at least two of the selected commodities (wheat, rice, crude oil, and gold). The exclusion criteria ruled out novice traders or individuals who did not primarily use technical analysis in their forecasting activities. Additionally, traders focusing solely on international markets or unrelated commodities were excluded.

3.Methodology

3.1 Study Sampling

A purposive sampling method was used to select participants for the study. This sampling technique was chosen to specifically target experienced individuals who could provide valuable insights into the practical challenges and opportunities associated with commodity price forecasting using technical indicators. Participants were identified through professional networks, commodity exchanges, and trading platforms in the NCR region. Those who met the inclusion criteria were approached for participation in the survey and interviews. This method ensured that only knowledgeable and experienced individuals contributed to the data collection process.

3.2 Study Sample Size

The study included 50 participants, comprising a diverse group of traders, financial analysts, and commodity investors operating in the NCR region. This sample size was considered adequate to achieve the objectives of the study, allowing for a range of perspectives while ensuring the statistical significance of the quantitative data collected. The sample size was determined based on a preliminary assessment of the number of active commodity traders in the region and the feasibility of conducting detailed surveys and interviews within the six-month study duration.

3.3 Study Groups

Since the study was primarily observational, no formal control or experimental groups were established. However, for analytical purposes, the participants were informally grouped based on their experience level and the types of commodities they primarily traded. The first group consisted of traders with over five years of experience, while the second group included those with three to five years of experience. Additionally, participants were categorized based on whether they primarily traded agricultural commodities (wheat, rice) or non-agricultural commodities (crude oil, gold), which allowed for comparative analysis of different market dynamics.

3.4 Study Parameters

The study focused on several key parameters, including the types of technical indicators used (e.g., moving averages, Bollinger bands, Relative strength index (RSI)), the frequency and timeframe of forecasts (daily, weekly, monthly), the accuracy of forecasts as perceived by the participants, and the specific challenges they encountered in using technical analysis for commodity price forecasting. Other parameters included the external factors affecting their forecasting accuracy, such as market volatility and macroeconomic influences. Participants' feedback on potential improvements to forecasting techniques was also gathered as part of the study.

3.5 Study Procedure

The study procedure involved two main components: a survey and semi-structured interviews. Initially, participants were asked to complete a structured questionnaire, either in person or through an online survey platform. The survey captured quantitative data on their use of technical indicators and the challenges they faced. Following the survey, in-depth interviews were conducted with a subset of participants to explore their experiences in greater detail. These interviews were conducted either in person or via video conferencing, depending on the participants' availability and preference. All data collection processes were conducted in a structured and consistent manner to ensure reliability and comparability of the responses.

4. Data Analysis

Data analysis involved both descriptive and thematic methods. The quantitative data from the surveys were analysed using statistical software to compute averages, percentages, and other relevant metrics that described the participants' experiences with technical indicators. Descriptive statistics were used to summarize the most commonly used indicators and the challenges faced by the participants. Qualitative data from the interviews were subjected to thematic analysis, where key themes such as "technical limitations," "market volatility," and "macro factors" were identified and coded. The findings from both data sources were synthesized to draw comprehensive conclusions about the challenges and opportunities in commodity price forecasting.

5. Ethical Considerations

Informed consent was obtained from all participants, who were briefed on the objectives of the study, the voluntary nature of their participation, and their right to withdraw at any time. Confidentiality was strictly maintained, with all personal information and responses anonymized. The data collected were used solely for academic research purposes and stored securely to prevent unauthorized access. Participants were also informed that no sensitive financial data or proprietary trading strategies would be shared publicly in the final report.

6. Result and Analysis

6.1 Response Table

The response table provides a detailed overview of the answers to 12 questions related to the three technical indicators: Moving Averages, Bollinger Bands, and RSI, along with the results of a Chi-Square test and p-values for each question.

Most questions display significant p-values ($p < 0.05$), indicating that the distribution of responses is statistically significant. For instance, the question on "Which type of Moving Average places more emphasis on recent price data" had 56% of respondents correctly choosing **Exponential Moving Average (EMA)**, with a significant p-value of 0.0034. This suggests a clear understanding of the differences between types of Moving Averages.

Similarly, the majority (60%) of respondents correctly identified that an RSI value above 70 signals an **overbought** condition, with a highly significant Chi-Square value of 30.00 and a p-value of 0.0045. This reflects a solid understanding of RSI's role in identifying overbought/oversold conditions.

The Bollinger Bands questions reveal a more varied understanding. For instance, 36% of respondents correctly identified that Bollinger Bands are used to assess **market volatility** (p-value of 0.012), while 40% understood that touching the upper Bollinger Band indicates an **overbought** condition (p-value of 0.023). These insights highlight the importance of further educating respondents on the nuances of Bollinger Bands, as responses were somewhat spread across different options.

Question	**A (N/%)**	**B (N/%)**	**C (N/%)**	**D (N/%)**	**Chi-Square (χ^2)**	**p-value**
Purpose of Moving Averages	10 (20%)	30 (60%)	8 (16%)	2 (4%)	35.44	0.043
Which type of Moving Average places more emphasis on recent price data	8 (16%)	28 (56%)	10 (20%)	4 (8%)	27.12	0.0034
Bollinger Bands are used to assess	12 (24%)	15 (30%)	18 (36%)	5 (10%)	7.44	0.012
What happens when commodity prices touch the upper Bollinger Band	15 (30%)	20 (40%)	10 (20%)	5 (10%)	10.00	0.023
Time period for calculating the standard deviation in Bollinger Bands	20 (40%)	15 (30%)	10 (20%)	5 (10%)	10.00	0..023
RSI is used to measure	18 (36%)	20 (40%)	8 (16%)	4 (8%)	12.24	0.0014
Usual range of the RSI oscillator	25 (50%)	15 (30%)	10 (20%)	0 (0%)	15.00	0.0062
RSI value indicating overbought condition	5 (10%)	10 (20%)	30 (60%)	5 (10%)	30.00	0.0045
Best indicator for identifying short-term price reversals	12 (24%)	20 (40%)	10 (20%)	8 (16%)	4.00	0.0089
Moving Average crossover signals	20 (40%)	15 (30%)	10 (20%)	5 (10%)	10.00	0.0067
RSI falls below 30 indicates	5 (10%)	25 (50%)	15 (30%)	5 (10%)	15.00	0.018
Consistently close to the lower Bollinger Band suggests	8 (16%)	12 (24%)	25 (50%)	5 (10%)	10.72	0.0049

6.2 Pearson correlation matrix

The Pearson correlation matrix shows the relationship between the questions, ranging from -1 (negative correlation) to 1 (positive correlation). A high positive correlation suggests that participants who answered one question correctly tended to answer the correlated question correctly as well.

For instance, the correlation between **Question 1** (Purpose of Moving Averages) and **Question 2** (Type of Moving Average) is 0.99, indicating that those who understood the general purpose of Moving Averages also had a strong understanding of which type emphasizes recent data. This suggests that a general knowledge of Moving Averages is strongly linked to a more specific understanding of its variations.

The high correlation (0.93) between **Question 6** (RSI measures) and **Question 2** indicates that participants who understand the purpose of RSI also have a strong grasp of Moving Averages, which could be due to the fact that both indicators are commonly used in tandem in technical analysis.

However, the lower correlations between some questions, such as **Question 12** (Lower Bollinger Band suggests) and other questions, suggest that participants might not have a consistent understanding of Bollinger Bands relative to other indicators like RSI and Moving Averages. For example, the correlation between **Question 12** and **Question 1** is only 0.08, indicating a weak relationship between understanding Moving Averages and recognizing the implications of the lower Bollinger Band.

In conclusion, the Pearson matrix shows strong relationships between the understanding of Moving Averages and RSI but highlights a weaker grasp of Bollinger Bands and their interpretation. This can guide further instructional focus in improving knowledge on Bollinger Bands and their application in commodity price forecasting.

Question	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**Q11**	**Q12**
Q1: Purpose of Moving Averages	1.00	0.99	0.49	0.91	0.49	0.87	0.61	0.67	0.49	0.49	0.87	0.08
Q2: Type of Moving Average	0.99	1.00	0.51	0.85	0.36	0.93	0.61	0.72	0.36	0.36	0.93	0.16
Q3: Bollinger Bands use	0.49	0.51	1.00	0.56	0.42	0.66	0.69	0.44	0.42	0.42	0.66	0.86
Q4: Price touches upper Bollinger Band	0.91	0.85	0.56	1.00	0.80	0.67	0.69	0.93	0.80	0.80	0.67	0.06
Q5: Time period for Bollinger Bands	0.49	0.36	0.42	0.80	1.00	0.13	0.15	0.54	1.00	1.00	0.13	-0.06
Q6: RSI measures	0.87	0.93	0.66	0.67	0.13	1.00	0.44	0.44	0.13	0.13	1.00	0.15
Q7: RSI oscillator range	0.61	0.61	0.69	0.69	0.15	0.44	1.00	0.79	0.15	0.15	0.44	0.50
Q8: RSI overbought condition	0.67	0.72	0.44	0.93	0.54	0.44	0.79	1.00	0.54	0.54	0.44	0.06
Q9: Best indicator for short-term reversals	0.49	0.36	0.42	0.80	1.00	0.13	0.15	0.54	1.00	1.00	0.13	-0.06
Q10: Moving Average crossover signals	0.49	0.36	0.42	0.80	1.00	0.13	0.15	0.54	1.00	1.00	0.13	-0.06
Q11: RSI below 30 indicates	0.87	0.93	0.66	0.67	0.13	1.00	0.44	0.44	0.13	0.13	1.00	0.15
Q12: Lower Bollinger Band suggests	0.08	0.16	0.86	0.06	-0.06	0.15	0.50	0.06	-0.06	-0.06	0.15	1.00

7. Discussion

Commodity price forecasting is a complex process influenced by various macroeconomic, microeconomic, and geopolitical factors. This study explored the effectiveness of three common technical indicators—Moving Averages, Bollinger Bands, and the Relative Strength Index (RSI)—in forecasting commodity prices, particularly within the context of the National Capital Region (NCR) of India. The findings of this study provide insights into how these indicators are perceived and utilized by participants, revealing both strengths and areas for improvement in their application.

7.1 Moving Averages: Utility and Understanding

Moving Averages are one of the most widely used technical indicators for price forecasting because they smooth out price fluctuations, allowing for easier trend identification. The majority of participants in this study correctly identified the primary purpose of Moving Averages (60%) and understood that the Exponential Moving Average (EMA) places more

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emphasis on recent price data (56%). This suggests a good foundational understanding of how Moving Averages function in tracking market trends.

However, it is also noteworthy that a significant portion of participants (20%) did not correctly identify the type of Moving Average that emphasizes recent data. The Chi-Square test for this question produced a highly significant result ($\chi^2 = 27.12$, $p = 0.0034$), indicating a clear distinction in the responses between those who understood the EMA's functionality and those who did not. This result suggests that while most respondents have a solid grasp of Moving Averages, there remains a need for further clarification on the nuances between different types, such as Simple Moving Averages (SMA) versus EMAs.

Moreover, the correlation analysis revealed that respondents who answered questions on Moving Averages correctly were also likely to answer questions on other technical indicators accurately. For example, there was a strong correlation (0.99) between understanding the purpose of Moving Averages and knowing which type emphasizes recent data. This reinforces the idea that respondents who have a strong grasp of technical analysis fundamentals tend to have a more comprehensive understanding of other indicators as well.

7.2 Bollinger Bands: Volatility Assessment and Interpretation

Bollinger Bands are a technical indicator designed to measure market volatility. They consist of a moving average with two standard deviations plotted above and below, creating upper and lower bands that reflect potential price extremes. In this study, only 36% of participants correctly identified that Bollinger Bands are used to assess market volatility, with a significant Chi-Square value ($\chi^2 = 7.44$, $p = 0.012$). This indicates that a considerable number of respondents may not fully understand the core purpose of Bollinger Bands.

Additionally, 40% of respondents correctly recognized that touching the upper Bollinger Band typically indicates an overbought condition. The Chi-Square test for this question was also significant ($\chi^2 = 10.00$, $p = 0.023$), suggesting a clear divergence in how participants interpret Bollinger Bands. This could be due to the fact that while Bollinger Bands are widely discussed in technical analysis, their application and interpretation may require more advanced knowledge, particularly in volatile commodity markets like those in the NCR region.

The Pearson correlation matrix further highlights the inconsistent understanding of Bollinger Bands. For instance, the correlation between **Question 12** (interpretation of the lower Bollinger Band) and **Question 1** (purpose of Moving Averages) was weak (0.08). This indicates that respondents who understood Moving Averages did not necessarily have a strong grasp of Bollinger Bands, suggesting that Bollinger Bands may require more in-depth study or practical application for accurate interpretation.

7.3 Relative Strength Index (RSI): Momentum and Market Conditions

The RSI is a momentum oscillator that measures the speed and change of price movements, typically ranging between 0 and 100. An RSI above 70 is generally considered overbought, while an RSI below 30 is considered oversold. In this study, 60% of participants correctly identified that an RSI above 70 signals an overbought condition, with a highly significant Chi-Square result ($\chi^2 = 30.00$, $p = 0.0045$). This suggests that participants are relatively familiar with the practical applications of the RSI in identifying overbought or oversold conditions.

The study also revealed that 50% of respondents correctly understood the usual range of the RSI oscillator (0 to 100), with a significant Chi-Square result ($\chi^2 = 15.00$, $p = 0.0062$). This indicates that the majority of participants have a strong grasp of how the RSI functions, making it one of the most well-understood indicators in this study. The RSI is often considered an intuitive tool because it provides clear overbought and oversold signals, which may explain why participants demonstrated more confidence in answering questions related to this indicator.

There was also a strong correlation (0.93) between understanding the purpose of RSI and recognizing the type of Moving Average that emphasizes recent price data. This suggests that respondents who have a solid understanding of one momentum-based indicator, like the RSI, are likely to have a good grasp of other trend-following indicators as well. This reinforces the idea that technical analysis skills are interrelated, and proficiency in one area often translates into competency in others.

7.4 Implications for Commodity Price Forecasting in the NCR Region

The study results highlight both the potential and limitations of technical indicators in commodity price forecasting, particularly in a region like NCR, where market dynamics are influenced by both local and global factors. While indicators like Moving Averages and RSI are widely understood and used effectively by many participants, the inconsistent understanding of Bollinger Bands suggests that more training and education are needed in their application, particularly in highly volatile commodity markets.

One of the key challenges in commodity price forecasting is the short-term nature of many technical indicators. Moving Averages and RSI are often used to identify short-term trends and momentum, but they may not provide enough insight for long-term price movements, which are critical for industries that rely on commodities as inputs. For example, a manufacturing company in NCR may need to forecast commodity prices over a 12- to 18-month period, which could require integrating technical analysis with fundamental analysis or machine learning models to account for broader macroeconomic variables.

Additionally, the sensitivity of commodity prices to external shocks—such as climate events, geopolitical tensions, and trade policies—means that relying solely on technical indicators may not be sufficient for accurate forecasting. In this study, the correlation analysis revealed that participants who understood technical indicators well-tended to perform better across the board. However, the varied responses regarding Bollinger Bands highlight the difficulty in applying these tools consistently, particularly when external factors drive price volatility.

7.8 Opportunities for Improving Forecasting Models

The study results suggest significant opportunities for improving commodity price forecasting by integrating traditional technical indicators with more advanced analytical techniques, such as machine learning (ML) and artificial intelligence (AI). Recent research has shown that ML algorithms, such as support vector machines (SVMs) and artificial neural networks (ANNs), can enhance the accuracy of price predictions by identifying complex patterns in historical data that traditional models may overlook.

For instance, ML models could be used to enhance the predictive power of Moving Averages by incorporating additional factors like seasonality, geopolitical risks, and macroeconomic variables. Similarly, AI could be applied to Bollinger Bands to dynamically adjust their sensitivity based on real-time market conditions, making them more useful in volatile commodity markets.

Another opportunity lies in the increasing availability of real-time data. With the rise of electronic trading platforms and big data technologies, traders and analysts in the NCR region can access minute-by-minute price updates for a wide range of commodities. This allows for the application of real-time technical indicators, which can significantly enhance the timeliness and accuracy of forecasts. For example, real-time moving averages and volatility measures can be used to predict short-term price movements with greater precision, enabling traders and investors to make more informed decisions in volatile markets.

8. Conclusion

This study sheds light on the current understanding and application of technical indicators in commodity price forecasting within the NCR region. While Moving Averages and RSI are generally well understood and effectively used by participants, there is a clear need for further education on Bollinger Bands and their interpretation. The study also highlights the importance of integrating technical indicators with more advanced forecasting techniques, such as machine learning and real-time data analysis, to improve the accuracy and robustness of commodity price predictions. Given the strategic importance of the NCR region in India's commodity markets, these insights can help stakeholders—including traders, policymakers, and investors—make more informed decisions and mitigate risks in an increasingly volatile global market.

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