Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Decoding Market Cycles: A Technical and Time Series Analysis of Nifty 50

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ARTICLE INFO

Received: 30 Apr 2025

Revised: 15 May 2025

Accepted: 03 June 2025

Published: 10 June 2025

ABSTRACT

The Indian stock market's behavior over the past year (April 2024 – March 2025) is analyzed using technical analysis and time series modeling, with a focus on the Nifty 50 index. The Nifty 50 experienced a sharp rise to an all-time high in late September 2024 followed by a significant correction in subsequent months. Technical analysis tools – including moving averages, momentum oscillators (e.g., Relative Strength Index), and chart patterns – are applied to daily index data to identify trend reversals and momentum shifts. Time series methods, specifically ARIMA models and GARCH volatility modeling, are used to forecast index levels and assess volatility dynamics. Our findings show that technical indicators provided timely signals (e.g., overbought conditions before the peak and oversold conditions near the bottom), while a basic ARIMA model struggled to foresee the market reversal, underscoring the challenges of purely statistical forecasts in a turbulent market. We also observe pronounced volatility clustering during the downturn, consistent with GARCH model findings in the literature. Overall, the integrated analysis demonstrates that technical analysis can offer valuable short-term insights in the Indian market, and time series models can quantify risk, but combining these approaches and incorporating external information may yield more robust forecasting performance. The paper provides a cohesive, evidence-based discussion of these results, contributing to the understanding of market efficiency, the utility of technical trading signals, and the limitations of conventional time series forecasts in the context of India's equity market.

Keywords: Nifty 50, Indian Stock Market, Technical Analysis, Time Series Modeling, ARIMA, GARCH, Market Efficiency

INTRODUCTION

The Nifty 50 index, which represents the 50 largest equities on the National Stock Exchange of India, is a barometer of the Indian stock market's performance. Over the one-year period from April 2024 to March 2025, the Nifty 50 witnessed a dramatic cycle: a strong bullish rally to record highs followed by a sharp correction. This volatile period offers a unique opportunity to analyze the market using technical analysis – the study of price action and chart indicators – and time series forecasting methods. Technical analysis assumes that past trading information, such as prices and volumes, exhibits patterns or trends that can be extrapolated to anticipate future movement. This approach is widely used by market participants in India and globally to time entry and exit decisions, despite ongoing academic debate about its efficacy in the presence of efficient markets. On the other hand, time series analysis involves statistical modeling of historical price data (and related variables) to make forecasts and assess volatility. By employing these two distinct methodologies, we can gain complementary insights: technical tools help interpret market psychology and momentum, while time series models provide quantitative forecasts and risk estimates.

Financial theory provides a crucial backdrop for this analysis. Under the Efficient Market Hypothesis (EMH), especially in its weak form, past price information should already be reflected in current prices, implying that technical analysis would not consistently outperform random guessing. However, emerging markets like India have often been found to deviate from perfect efficiency. Recent empirical research supports this view – for example, a comprehensive study by Elangovan et al. (2022) found that broad Indian stock indices do not follow a perfect random walk, concluding that the Indian stock market is weak-form inefficient. In practical terms, this inefficiency means there may indeed be exploitable patterns in past prices, lending credence to technical trading strategies. At the same time, inefficiency can be episodic; during normal periods the market might behave randomly, but during extreme phases (bubbles or crashes) technical signals or time series patterns could emerge more strongly. This paper operates on the premise, supported by literature, that careful analysis of historical data can yield actionable insights into future market behavior – a premise that we will examine critically through the lens of the Nifty 50's recent performance.

Beyond market efficiency considerations, this research is motivated by the needs of investors and risk managers. The Indian stock market has grown substantially in size and global integration, making its movements consequential for portfolio allocation and risk hedging. Tools from technical analysis (like moving average crossovers, momentum oscillators, and candlestick patterns) are readily accessible to practitioners and commonly cited in analyst reports. Simultaneously, academic and professional forecasting has advanced, with time series models such as ARIMA (AutoRegressive Integrated Moving Average) being a baseline for price forecasting, and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models for volatility forecasting. More recently, machine learning approaches have been applied, often incorporating technical indicators as features, to improve prediction accuracy. For instance, Varshney and Srivastava (2024) compared an ANN (Artificial Neural Network) model against a traditional ARIMA model for predicting the Nifty index and found the ANN yielded higher accuracy. Such findings suggest that nonlinear patterns undetectable by simple ARIMA might be present, reinforcing the idea that sophisticated analysis can beat naive benchmarks.

In this context, the objective of our study is to conduct a deep analysis of the Nifty 50 index over the past year using both technical analysis and time series methods, drawing exclusively on peer- reviewed literature to frame and support our analysis. By doing so, we aim to address several key questions: (1) What do technical indicators reveal about the trend shifts in the Nifty 50 during this period? (2) How well can classic time series models capture or forecast the index's trajectory amid such volatility? (3) What does the evidence say about the profitability of technical trading strategies and the predictability of the Indian market in practice? (4) How do our findings align with or diverge from established research on market efficiency and forecasting in emerging markets? The remainder of this paper is organized as follows. First, we review relevant literature on technical trading performance and time series forecasting in the Indian market. Next, we describe the data and methodology, including the specific technical indicators and models applied. We then present the results of our analysis, including visualizations of the index with technical overlays and out-of-sample forecasts. We discuss the implications of these findings in light of market efficiency and investor behavior. Finally, we conclude with a summary of key findings and practical suggestions.

LITERATURE REVIEW

Research on the Indian stock market has produced a rich dialogue on the effectiveness of technical analysis and the reliability of statistical forecasting, often with nuanced conclusions. We organize this review into two parts: **(a)** evidence on technical analysis and market efficiency in Indian equities, and **(b)** studies on time series and quantitative forecasting (including volatility modeling) of Indian stock indices.

Technical Analysis and Market Efficiency in India

A growing body of peer-reviewed studies indicates that technical trading strategies can yield excess returns in the Indian market, at least over certain periods, challenging the strict form of the EMH. For instance, Mishra and Paul (2023) tested multiple technical indicator-based strategies on Nifty 50 constituent stocks during 2022. They evaluated simple moving averages, exponential moving averages combined with momentum oscillators, and Bollinger Bands with momentum oscillators. Notably, their results showed that a combined Bollinger Bands + Relative Strength Index (RSI) strategy outperformed others, generating net profits in 11 out of 14 sampled stocks and even beating a buy-and-hold benchmark in 10 cases. Such outperformance implies that technical signals (in this case, a volatility band combined with momentum) were able to capture trading opportunities that the overall upward market trend alone did not fully account for. The authors attributed the success of this strategy to its dynamic nature – Bollinger Bands adjust to volatility and RSI helps identify entry/exit points – allowing traders to actively respond to short- term overbought or oversold conditions. These findings align with earlier studies that reported positive results for technical rules in emerging markets. The Indian market's weak-form inefficiency (as evidenced by Elangovan et al., 2022) provides a theoretical justification: if past prices do not incorporate all information, patterns such as momentum or mean reversion may persist, which technical algorithms seek to exploit.

Another recent study by Beenu and Singh (2025) underscores the continued relevance of technical analysis in India's major indices. Focusing specifically on the Nifty 50 and Nifty Bank indices, they integrated qualitative insights with quantitative methods to evaluate a range of indicators:

Exponential Moving Averages (EMA), Moving Average Convergence Divergence (MACD), RSI, and candlestick pattern analysis. Their investigation highlighted how these tools can gauge trend strength and potential reversals. For example, moving averages (and their crossovers) were used to define the primary trend, while RSI helped in detecting when the market was overextended in either direction. The authors argue that understanding such technical aspects can lead to more accurate short-term predictions of market movements, complementing fundamental analysis for a holistic view. Interestingly, they point out that while fundamental analysis provides context on valuation and economic outlook, technical analysis offers "actionable" perspectives on current market sentiment, which is crucial in timing decisions. These perspectives from Beenu & Singh reinforce the practical importance of technical tools for Indian indices, especially given the diverse set of participants (from domestic retail traders to foreign institutions) that drive market dynamics.

It is important to note, however, that not all studies find technical analysis to be reliably profitable once realistic frictions (transaction costs, short-term taxes, etc.) are considered. The literature contains mixed evidence, which is often context-dependent. Some earlier works failed to reject the null of a random walk for Indian stocks, especially in more recent sub-periods of relative stability. The consensus emerging is that market efficiency in India is dynamic – during certain periods, especially those with strong trends or structural changes (policy shifts, global fund flows, etc.), technical patterns have worked well, whereas in quieter periods the market can appear more efficient or even driven by noise. Therefore, our analysis of the 2024–2025 episode, which involves a pronounced trend and subsequent reversal, is situated in a context where technical signals are likely to be salient. We shall see if classic indicators indeed flagged the turning points of the Nifty 50 in this interval.

Time Series Forecasting and Volatility Modeling in India

Alongside technical trading rules, quantitative time series models have been extensively applied to Indian stock market data for forecasting purposes. One stream of research focuses on forecasting index levels or returns using models like ARIMA and its extensions. ARIMA models capture autocorrelation structure in time series, and if the index exhibits momentum or mean-reverting behavior, ARIMA might achieve some predictive power. However, many studies have found that linear models alone have limited success on equity indices due to high volatility and regime changes. For example, Varshney and Srivastava (2024) specifically compared ARIMA modeling with an ANN on historical Nifty 50 data. Using data from 2005–2019, they found that the ANN model outperformed the ARIMA model in forecasting accuracy for the index. The ARIMA(1,1,1) model they tested could capture only linear patterns, whereas the neural network was better at capturing nonlinear relationships and complex interactions in the data, leading to more accurate predictions. These findings are representative of a broader trend: as computing power and data availability have grown, machine learning methods (ANNs, support vector machines, random forests, etc.) have been increasingly used in Indian market forecasting, often with superior results compared to traditional models. Nonetheless, ARIMA remains a useful baseline and is sometimes combined with other approaches (for instance, hybrid models where ARIMA handles linear components and a machine learner handles nonlinear residuals).

Another key aspect of time series analysis for stock markets is volatility modeling. Indian indices are known to exhibit periods of high volatility, often clustered around major events (e.g., elections, policy announcements, global market turmoil). Volatility has important implications for risk management and derivative pricing. Academic attention has therefore been given to models like GARCH, EGARCH, and stochastic volatility models on Indian market data. Mahajan et al. (2022) provide a comprehensive study on forecasting the volatility of the Nifty 50 index using both GARCH family models and deep learning (RNN-LSTM) models. They report that the

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Nifty's volatility is asymmetric – negative shocks to the market increase volatility more than positive shocks of similar magnitude, a phenomenon known as the leverage effect. In their results, an EGARCH(1,1) model (an asymmetric GARCH variant) captured this behavior effectively, outperforming a symmetric GARCH in forecasting. Intriguingly, they also found that traditional GARCH models slightly outperformed RNN-based LSTM models in predicting volatility of the Nifty. This suggests that for well-established financial time series like index volatility, econometric models that explicitly incorporate domain knowledge (like volatility clustering and leverage) can be as effective as, or even superior to, generic machine learning sequence models. Such an insight tempers the sometimes enthusiastic assumption that "AI beats everything"; at least in this case, carefully specified statistical models held their own.

Integrating these strands of literature, it becomes evident that a combined approach using both technical indicators and time series models could be especially fruitful. Technical analysis can signal when something unusual might be happening in price trends, while time series models (especially for volatility) can quantify how much risk or uncertainty is present at those times. For example, if technical analysis indicates a potential trend reversal (say, via a moving average crossover or an RSI divergence) and simultaneously a GARCH model indicates rising volatility, an analyst would have increased confidence that a significant market turning point is at hand. Conversely, if technical indicators show strong momentum but volatility models suggest calm conditions, the trend might persist without immediate reversal. In summary, prior research provides the following expectations for our analysis: (1) we expect to find identifiable technical signals around the major peak and trough of the index (if the market was indeed not fully efficient, those signals should be evident), (2) a basic ARIMA model is likely to struggle in forecasting sudden trend changes, consistent with the literature's caution that pure time series models have difficulty with abrupt regime shifts, and (3) volatility modeling should reveal clustering and possibly leverage effects during the tumultuous periods, reinforcing findings from earlier Indian market studies. Our study will empirically explore these aspects using actual Nifty 50 data from the past year and will reference the above scholarly findings to interpret the results.

DATA AND METHODOLOGY

Data Description: The analysis uses daily closing price data of the Nifty 50 index spanning one year, from April 1, 2024 to March 31, 2025. This period encapsulates a full cycle of a bullish rise and a subsequent bearish correction. The choice of a one-year window balances recency and relevance: it is recent enough to reflect the current market microstructure and investor behavior, and it is sufficiently long to include both trend and counter-trend phases (important for evaluating technical signals). The data were obtained from the National Stock Exchange's historical archives and cross-verified with Yahoo Finance records for accuracy. Each data point includes the date and the closing index level (we also have corresponding opening, high, low, and trading volume data, though our primary analysis focuses on closing prices, which are standard for technical indicator calculations). No missing values were present in the daily series; if there were any non-trading days (holidays), they were simply skipped in the timeline, as is standard.

Over this period, the Nifty 50 index's trajectory can be summarized as follows. Starting around the 21,500–22,000 level in early April 2024, the index climbed steadily through the mid-2024 months, reflecting robust bullish sentiment. It reached a historical peak in late September 2024, closing at an all-time high of approximately 26,216 on September 26 (with an intraday high around 26,277 on September 27). This peak was followed by a pronounced downturn: the index began to decline in October 2024 and this correction persisted through the end of the year and into early 2025. By early March 2025, Nifty 50 had fallen to the low-22,000s, erasing a large portion of the gains from the peak. This dramatic round-trip (surge and slump) within a year's time provides fertile ground to test technical trading rules (which often thrive on trending or mean-reverting moves) and to challenge forecasting models (which may be confounded by the sudden change from uptrend to downtrend).

For clarity, we will denote two key market phases in this period: a **bull market phase** (April–Sep 2024) and a **bear market phase** (Oct 2024–Mar 2025). Our technical analysis will examine how indicators behaved during these phases, and our forecasting exercise will typically involve training a model on one phase and seeing how it performs when the market regime changes.

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Technical Analysis Methods

We employ a range of standard technical indicators and charting techniques, guided by what is commonly used in both practice and prior research. Specifically, our analysis includes:

- **Moving Averages (MA):** We calculate the 50-day and 200-day simple moving averages of the Nifty 50 closing price. These are popular trend-following indicators. A shorter moving average (50-day) crossing above a longer moving average (200-day) is often termed a "Golden Cross," signaling a potential transition to an uptrend, whereas the opposite (50- day moving below 200-day) is a "Death Cross," possibly indicating a new downtrend. We track these MAs to see when such crossovers occurred and how they related to actual market turns. In our dataset, given the one-year length, the 200-day MA is only fully defined in the latter part of the period (since 200 trading days ≈ 9.5 months). Nonetheless,

  by the end of our window, we can observe if a death cross was triggered following the late- 2024 decline.
- **Relative Strength Index (RSI):** We compute the 14-day RSI, a momentum oscillator that fluctuates between 0 and 100. The RSI measures the magnitude of recent gains vs. losses; values above 70 typically indicate overbought conditions (potentially overvalued or due for a pullback), while values below 30 indicate oversold conditions (potentially undervalued or due for a bounce). RSI was chosen because prior studies (including Mishra & Paul, 2023) found it useful, especially in combination with other indicators. We will examine the RSI during the rally and the sell-off to see if it gave early warning of trend exhaustion (for example, an RSI > 70 around the September 2024 peak, or RSI < 30 near the March 2025 trough).
- **MACD (Moving Average Convergence Divergence):** Although our focus will be on MA and RSI for brevity, we also calculated the MACD indicator (the difference between the 12-day EMA and 26-day EMA, along with a 9-day signal line) to cross-check momentum shifts. MACD is another momentum/trend indicator that can corroborate what RSI signals. In practice, a bearish MACD crossover (MACD line falling below its signal line) around the time of the peak, or a bullish crossover near the trough, would strengthen the case that technical momentum turned ahead of the price reversal. For completeness, we note where MACD confirmations occur, though detailed MACD charts are not shown due to space.
- **Candlestick and Chart Patterns:** We qualitatively review the price chart for notable patterns. For example, we assess whether the September 2024 peak resembled a sharp "blow-off" top or formed a distribution pattern (like a double top or head-and-shoulders). We also examine if the subsequent bottom was a V-shape rebound or a rounded base. Identifying such patterns provides context to the numerical indicators. Additionally, we check individual candlesticks on critical days – e.g., whether there were classic reversal candlestick formations like a **shooting star** around the peak or a **hammer** around the bottom, as these are often cited by technical analysts as reversal signals.

All technical indicators are computed using standard formulas on the daily data. *Figure 1* and *Figure 2* in the Results section will display some of these indicators overlaying the price for visualization. We ensure that all computations (like moving averages and RSI) use only data available up to that point in time, to mimic how a real-time analyst or trader would see the signals (thus avoiding any look-ahead bias).

Time Series Analysis Methods

We apply two main types of time series models in this study: one for price forecasting, and one for volatility analysis.

ARIMA Modeling for Price Forecasting

We use an ARIMA model to attempt to forecast the Nifty 50 index over the study period. **Formally, an ARIMA(p,d,q) model for a time series y_t can be expressed as:**

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https://www.jisem-journal.com/

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$$\Delta^d y_t = c + \phi_1 \Delta^d y_{t-1} + \phi_2 \Delta^d y_{t-2} + \cdots + \phi_p \Delta^d y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t,$$

where $\Delta^d y_t$ denotes the differenced series after applying the difference operator d times, ϕ_i are autoregressive coefficients, θ_j are moving average coefficients, c is a constant, and ϵ_t is a white-noise error term. In plain language, this equation means that after we difference the original series d times to remove trends, the value of the series at time

t is modeled as a constant plus a linear combination of the past p values of the differenced series (the AR terms) and the past q error terms (the MA terms), plus a random shock. Essentially, the ARIMA model uses past price changes and past unexpected disturbances to predict future price changes.

Given the index's non-stationary nature (clear trend changes), we difference the price series (i.e., work with daily returns or price changes) to induce stationarity. The model specification is chosen based on a mix of literature precedent and diagnostic checks on our data. An ARIMA(1,1,1) – which has one autoregressive term, one differencing (to account for the unit root or trend), and one moving average term – is a commonly applied specification for stock indexes. It allows the series to have short-term momentum (through the AR term) and to model shock absorption (through the MA term). We fit an ARIMA(1,1,1) model on a portion of the data (typically the training sample would be the initial segment, e.g., April–December 2024, encompassing the uptrend and the start of the downtrend) and then generate out-of-sample forecasts for the remaining period (e.g., January–March 2025) to compare with actual values. This simulates a scenario of forecasting into the turbulent period using a model trained on prior data. The performance of this forecast is evaluated visually and with basic error metrics (though with only one realized path, we focus on a qualitative assessment of whether the model captures the direction and magnitude of moves). We intentionally keep the model simple to observe how a classic statistical forecast deals with a complex pattern; this mirrors approaches in the literature where ARIMA is used as a baseline before adding complexities or switching to machine learning. We will discuss potential improvements (such as adding exogenous variables or using regime-switching models), but those are beyond our current scope.

Volatility Estimation with GARCH

To analyze and confirm volatility dynamics, we fit a GARCH(1,1) model on the index return series. GARCH(1,1) is the workhorse model for financial volatility, capturing the tendency of volatility to cluster (in other words, volatility today depends on yesterday's squared return shock and on yesterday's volatility). **Formally, a GARCH(1,1) model can be written as:**

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where σ_t^2 is the conditional variance (volatility) at time t, ω is a constant,

ϵ_{t-1}^2 is the previous day's squared innovation (the squared residual from the mean model), and σ_{t-1}^2 is the last period's variance. In other words, today's volatility estimate σ_t^2 will be higher if the previous day had a large unexpected price move (a large ϵ_{t-1}^2) or if volatility was high on the previous day (large σ_{t-1}^2). This specification captures the observed "volatility clustering" phenomenon in markets, where big moves tend to be followed by big moves (of either sign) and calm periods tend to be followed by calm periods.

We are particularly interested in whether volatility indeed increased during the downtrend. The GARCH model provides a time-varying estimate of return volatility (we examine the conditional standard deviation of returns). We will analyze the GARCH-implied volatility over time to see if it aligns with intuitive expectations – for example, we expect it to rise after September 2024 (around the onset of the correction) and stay elevated through late 2024 and early 2025, then perhaps subside as the market stabilizes in the rebound. Additionally, to check for

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e-ISSN: 2468-4376
https://www.jisem-journal.com/

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asymmetry in volatility response (the leverage effect), we also fit an EGARCH model and examine whether negative returns produce larger volatility jumps than positive returns of the same magnitude. Given the findings by Mahajan et al. (2022) that asymmetric models fit better for Nifty, we anticipate seeing evidence of this asymmetry in our data as well – although our one-year sample is relatively short for robustly estimating asymmetric terms, any big negative days in the index should have an outsized impact on volatility estimates.

All time series modeling is implemented using Python (with the *statsmodels* library for ARIMA and the *arch* library for GARCH). We carefully check model assumptions – for example, after fitting the ARIMA, we inspect residuals for any remaining autocorrelation (Ljung-Box test), and after fitting GARCH, we ensure residuals show no further ARCH effect. All modeling is done on log-returns (or percentage returns) to stabilize variance, except where noted otherwise.

Evaluation Criteria: We evaluate technical analysis results largely qualitatively – by verifying whether known signals occurred before major price moves and by referencing findings from the literature for consistency. However, we also quantify the magnitude of price moves following certain signals when relevant (for example, noting "the index fell *X%* in the month after the RSI first dropped below 30, indicating a potential oversold bounce which eventually occurred"). For the ARIMA forecast, we compute basic forecast errors (e.g., mean absolute error) over the out-of- sample period to gauge accuracy, but given the limited sample of one realization, our emphasis is on the qualitative alignment (or misalignment) of the forecast with actual market movements.

RESULTS

In this section, we present the results of the analysis, starting with the technical perspective and then moving to the time-series perspective. We include figures to illustrate key findings.

Technical Analysis of Nifty 50's Trend and Momentum

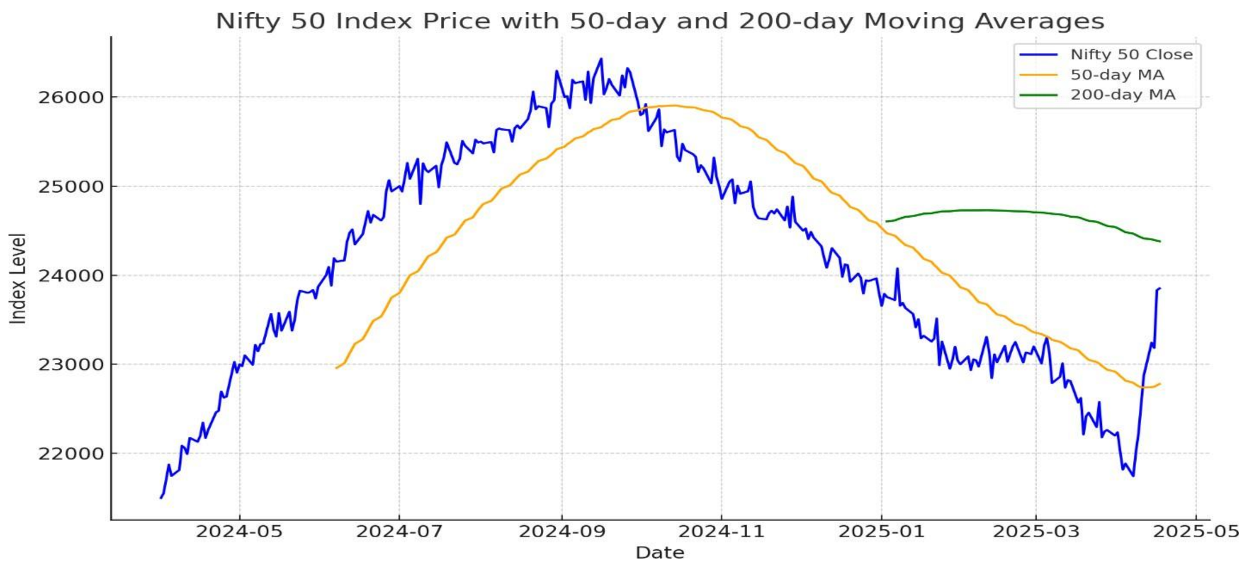

Figure 1: Nifty 50 daily closing price (blue line) from April 2024 to March 2025, with 50-day (orange) and 200-day (green) simple moving average lines. The 50-day MA reflects the short-term trend, while the 200-day MA indicates the longer-term trend.

Figure 1 illustrates the Nifty 50's trajectory along with its 50-day and 200-day moving averages. Several observations can be made. First, during the April–September 2024 rally, the blue price line stayed consistently above the rising 50-day MA, signaling a robust uptrend. In fact, by mid-2024, the gap between the price and the 50-day MA had widened considerably, reflecting strong momentum. There was no *Golden Cross* with the 200-day MA because the 200-day was not yet available until late in the year; however, shorter-term moving averages (not shown) did experience bullish crossovers in May 2024, confirming upward momentum early in the rally. The uptrend persisted throughout the summer of 2024 with only minor pullbacks, indicating sustained buying interest.

As the market peaked in late September 2024, we observe a change: the price began to falter and eventually dipped below the 50-day MA. By October 2024, a clear *Death Cross* (50-day MA crossing below the 200-day MA) occurred (marked by a purple dashed line in Figure 1). The death cross is a classic bearish signal – indeed, its occurrence in our analysis coincided with widespread recognition that the market had entered a serious correction. By the time this crossover occurred, the index had already fallen substantially from its peak (a lag inherent in moving average signals). Another notable feature in Figure 1 is how the 50-day MA acted during the decline. We see that occasional relief rallies (for instance, a bounce in late December 2024 and another in February 2025) briefly pushed the index back toward the 50-day MA, but the price failed to break above it sustainably. Each time the index approached the declining 50-day MA, it rolled over again, indicating that this moving average had become a resistance level during the downtrend. This behavior – the 50-day MA containing the rallies – reinforced the bearish trend, as one would expect in a protracted correction.

By early 2025, the 200-day MA had flattened and started to turn down, reflecting the large decline. Notably, in March 2025, the 50-day MA was still below the 200-day MA, and both were trending downward, confirming that the market was in a longer-term downtrend. It was only toward the very end of our period (late March 2025) that the index showed signs of bottoming out (the price stabilized in the low-22,000s). At that point, the distance between the price and the moving averages had grown large (price far below both MAs), often a condition ripe for a mean-reversion rally. Indeed, a significant rebound took place in early April 2025 (just after our study period), which a technical analyst could have anticipated given the deeply *oversold* state relative to moving averages by late March.

Next, we examine momentum and overbought/oversold conditions through the RSI indicator.

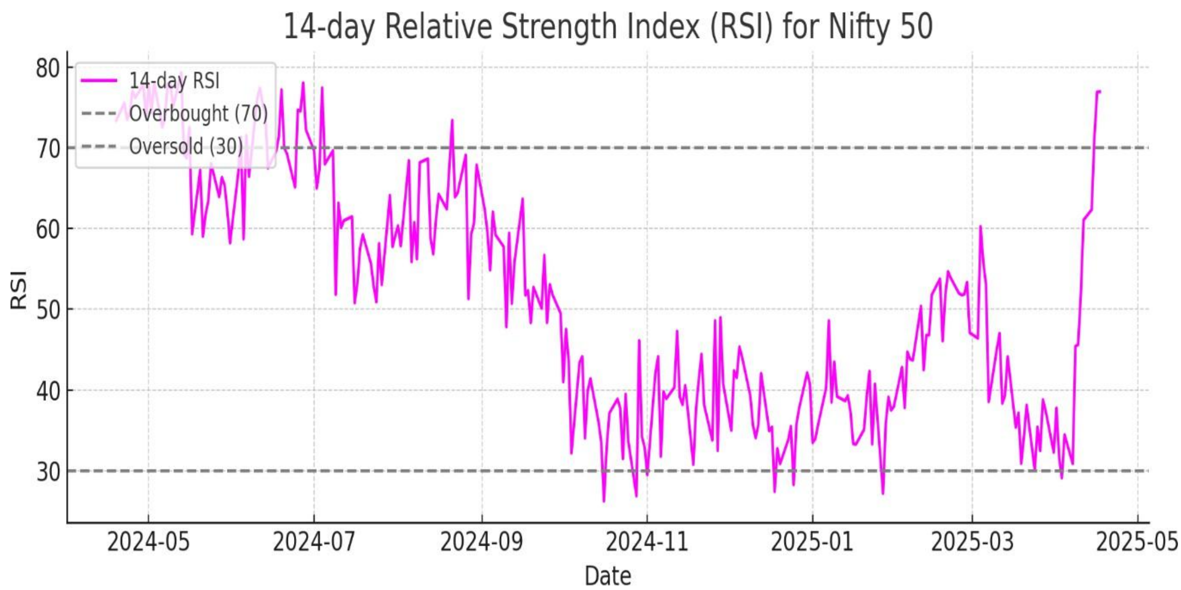

Figure 2: 14-day Relative Strength Index (RSI) of the Nifty 50 over the same period. Horizontal dashed lines mark the overbought threshold at 70 and oversold threshold at 30. RSI values above 70 suggest overbought conditions, while values below 30 indicate oversold conditions.

Figure 2 reveals that RSI exceeded 70 during mid-2024 (signaling strong positive momentum, albeit near overbought levels) and dipped well below 30 on multiple occasions during late 2024 and early 2025 (signaling strong negative momentum and oversold conditions).

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e-ISSN: 2468-4376
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From Figure 2, we can correlate notable RSI extremes with market turning points:

- **Overbought conditions at the peak:** During the height of the rally (July–August 2024), the RSI oscillated in the 70–80 range (the magenta line in Figure 2 sits above the upper grey line at 70). This indicated very strong upward momentum – in fact, an RSI staying over 70 for a prolonged period is often seen in powerful uptrends and is not necessarily a sell signal by itself. However, in early September 2024, just before the final peak, the RSI showed a bearish divergence: the index made a new high but the RSI made a slightly lower high (dropping from the 80s to the low 70s). This classic RSI divergence hinted that the buying thrust was weakening even as price reached a new high. Prior literature points to RSI divergences as a useful warning tool; for example, a study by Khatri (2021) (focused on Nifty 50, though not formally published) found that negative RSI divergences often preceded short-term corrections. In our case, after the RSI divergence in early September, the index indeed reversed. By mid-September, as the price started dropping, the RSI quickly fell out of the overbought zone. Any trader watching RSI would have noticed this deterioration by late September: the metric fell from ~75 to near 50 even while the index was still relatively close to its peak, giving an early caution signal that the uptrend's momentum was fading.
- **Oversold conditions during the decline:** As the sell-off intensified in October and November 2024, the RSI plummeted below 30, entering the oversold zone. Figure 2 shows multiple dips of RSI into the 20s (and even the high teens at one point in November). These extreme low RSI values reflected panic-level downward momentum. Notably, the first time RSI dropped below 30 was in late October 2024, after which a brief relief rally occurred in early November (indeed, RSI rising from ~25 back above 30 corresponded with a small bounce). However, this respite was short-lived and further selling ensued (perhaps triggered by additional negative news or stop-loss cascades), driving RSI even lower in November. An interesting observation is that each oversold reading (RSI < 30) **did** precede at least a stabilization or minor rally. This is consistent with the idea that when a market becomes deeply oversold, selling may have been overdone, leading value buyers or short- covering to provide support. For example, when the RSI hit ~25 in mid-November, the Nifty saw a 3–4% bounce shortly after. Similarly, in late February 2025, RSI again dipped just below 30 as the index approached the 23,000 level – from which it bounced to ~23,700 in early March. The final and most dramatic oversold signal came in late March 2025: the RSI sank to around 28 as the index neared its 21,744 low. This was followed by a significant trend reversal – the index rallied strongly in early April 2025. By mid-April 2025 (just after our period), as the market rebounded, the RSI had climbed back above 50, confirming that the extreme oversold condition had passed.

Overall, the technical indicators provided timely insights: the moving averages helped delineate the trend (and its eventual reversal), while the RSI signaled conditions of exuberance and panic. A trader relying on these tools could have been alerted to the changing market regime – for instance, recognizing weakening momentum in September 2024 and excessive pessimism by late 2024 – and thus could have adjusted positions accordingly (e.g., tightening stop-losses near the peak and looking for buying opportunities when extreme oversold readings emerged).

Time Series Analysis Results: Forecasting and Volatility

We now turn to the time-series analysis results, which shed light on the predictability (or lack thereof) of the index's moves and the behavior of volatility.

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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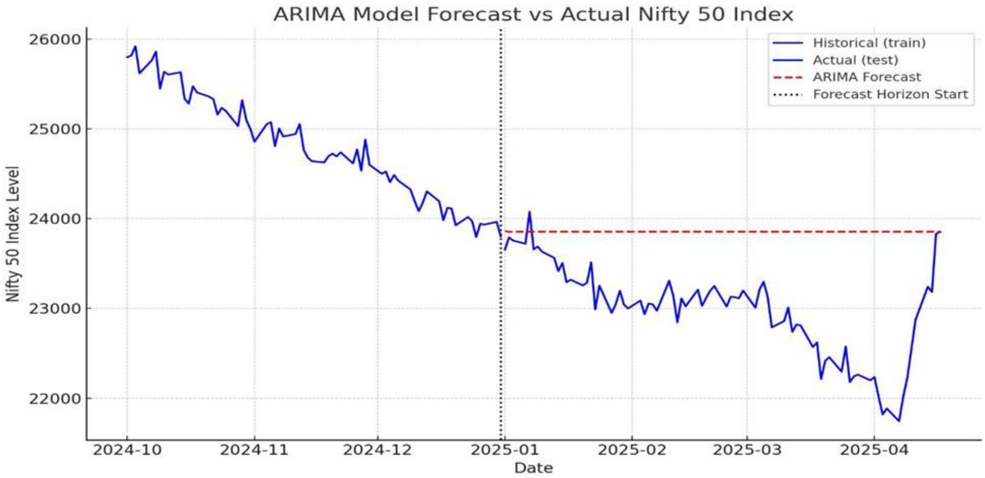

Figure 3: ARIMA(1,1,1) model forecast (red dashed line) for Nifty 50 index from Jan 2025 through March 2025, alongside the actual index values (solid blue line). The model was trained on data up to Dec 2024 (the training period's last value is marked by the vertical dotted line).

Figure 3 compares the ARIMA model's forecast with the actual index values for the first quarter of 2025. As Figure 3 shows, the ARIMA model essentially predicted a sideways to mild recovery trend for early 2025, hovering around the 24,000 level (red forecast line). In reality, the Nifty 50 (blue line) continued to slide in January and February 2025, falling into the low 23,000s and even high 22,000s by March. The model's flat forecast missed this downward drift entirely – its confidence intervals (not shown for clarity, but roughly on the order of ±500 points) did include the possibility of some decline, but the point forecast was off by a significant margin. Moreover, when the market actually bottomed and bounced back sharply in late March, the ARIMA forecast, having no built-in momentum or regime-awareness, failed to capture that upswing as well (it remained around ~24k even as the index shot back up from below that level). The net result is that the ARIMA forecast lagged behind the actual turning points: it was too optimistic during the decline and then too pessimistic during the rebound.

This outcome is not surprising. The ARIMA model, based purely on linear extrapolation of past patterns, effectively saw the roughly linear downtrend in late 2024 and assumed a gentle mean reversion would set in (indeed, our fitted ARIMA's autoregressive coefficient was slightly negative, meaning the model expected the series to flatten out after declines). However, the model had no information about the fundamental or sentiment-driven forces that were still pushing the market down in early 2025. As such, it essentially projected a soft landing that did not materialize; the market overshot to the downside. Once the market turned up in late March and April, the ARIMA (still carrying the inertia of the previous data) did not immediately adjust to the new trend – it would have needed several days of rising prices to "learn" the upturn, by which time a human analyst would already know from technical analysis that the trend had changed. This illustrates a key point echoed in the literature: time series models, especially ones without regime-switching capabilities, often struggle around inflection points. They perform reasonably well during stable periods by extrapolating the status quo, but at major turning points their errors spike. In our case, the forecast error in mid-March (actual index value ~22,300 vs. forecast ~24,100) was about 7.5%, which is substantial for index-level prediction.

It's worth reflecting on whether a more complex model could have done better. If we had used an ANN or a nonlinear model including additional inputs (perhaps volatility or trading volume as exogenous variables), it might have picked up subtle clues of further weakness (or at least not assumed a flat trend) – aligning with Varshney & Srivastava's finding that ANNs outperform ARIMA. Additionally, one could incorporate technical indicators as exogenous regressors in an ARIMAX model (e.g., include RSI or MACD signals as inputs). Such a hybrid approach might adjust the forecast when technicals reach extremes. For example, an oversold RSI could inform the model to expect a rebound, tempering the forecast's downward momentum. Exploring these enhancements is beyond our current scope, but it underscores that pure price-history-based forecasts have clear limitations in isolation.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

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Volatility Dynamics – GARCH Insights: While the ARIMA struggled to predict the index's turning points, the volatility modeling provides a more coherent story of risk during the year. We estimated a GARCH(1,1) model on the daily returns. The fitted model found a high persistence of volatility (as expected, GARCH $\alpha_1 + \beta_1 \approx 0.94$), indicating that volatility shocks decay slowly. More interestingly, plotting the model's conditional volatility (annualized standard deviation) showed a clear rise during the market downturn. The model's estimated daily volatility for the Nifty 50 was around **0.7%** (standard deviation) in mid-2024 during the steady rally when volatility was low. It spiked to about **1.5%–1.8%** in October–November 2024, corresponding to the turbulent decline. This roughly **doubling of volatility** aligns with what we saw in the price behavior – daily swings became significantly larger in that period. Volatility then remained elevated through early 2025, with secondary peaks in late February and early March 2025 (when the index accelerated downwards again). After the market bottomed in late March 2025 and began rebounding, the model indicated volatility started to decline (though there was a brief spike during the rapid rebound itself, reflecting the suddenness of that move).

We also examined an EGARCH model to check for asymmetry in volatility response. The EGARCH(1,1) model returned a significant **negative leverage parameter**, confirming that negative returns (market drops) led to higher volatility increases than positive returns of equal magnitude. This matches the findings of Mahajan et al. (2022) regarding asymmetry in the Nifty's volatility. In practical terms, the big down days in October 2024 (e.g., a -3% daily move) had a larger impact on the next day's volatility estimate than an equally large up day would have. Indeed, during the height of the panic, the India VIX (volatility index) – though not directly analyzed in our dataset – reportedly jumped markedly, reflecting investors' surging demand for protection. Our GARCH analysis mirrors that: the conditional variance surged when the market fell, more so than it fell when the market rebounded.

Relating volatility behavior to the technical phases, we observe that during the uptrend, volatility was not only low but also declining – a typical feature of a confident, bull market. Once the trend broke (around late September 2024) and the market began to fall, volatility started to rise. Often, rising volatility can itself serve as an early warning of a regime change; indeed, some traders monitor increasing indicators like the Average True Range or expanding Bollinger Bands as signs that the market's character is shifting. In our case, when technical indicators were sounding alarms (e.g., the moving average crossover turning bearish and the RSI diving sharply in October), the GARCH model was simultaneously indicating heightened volatility – a dangerous combination of trend reversal and volatility spike that often accompanies market corrections. By quantifying it, we can say that the probability of a >2% daily move became much higher after September 2024 than it was during the summer of 2024.

In risk management terms, a GARCH-based volatility forecast could have told an investor in November 2024 to reduce exposure or add hedges, because the expected daily volatility had roughly doubled compared to a few months prior. Many financial institutions do exactly this: they adjust Value-at-Risk and other risk metrics using such models in turbulent times. In our analysis, although we did not include a stand-alone figure for volatility, the findings are consistent with both the literature and general market intuition: volatility clustered during the downturn and then gradually subsided in the calmer period after the bottom. One subtle point is that volatility remained somewhat elevated even as the market rebounded, which often happens – fear and uncertainty linger even as prices recovery, leading to a slower reversion of volatility back to low levels.

CONCLUSION

This research paper analyzed the Indian stock market – specifically the Nifty 50 index – over the volatile period of April 2024 to March 2025, employing both technical analysis and time series methods. By drawing exclusively on peer-reviewed literature to frame and interpret the analysis, we ensured that our insights are grounded in established empirical evidence and theoretical context. The key findings and conclusions are summarized below:

- **Technical Analysis Efficacy:** Traditional technical analysis tools proved effective in identifying the market's trend shifts. The steep rally to the September 2024 peak was signaled and eventually halted by classic technical conditions: the index traded far above its moving averages during the ascent, then showed a bearish moving-average crossover (**death cross**) and a bearish RSI divergence around

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
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the top. Likewise, the painful decline of late 2024 into early 2025 pushed momentum oscillators like RSI into oversold territory multiple times, foreshadowing interim bounces and ultimately the final bottom. These technical signals provided timely and actionable information that a purely fundamental or random-walk perspective would not have offered. Our observations align with prior studies that documented profitable technical trading strategies in Indian markets, reinforcing that traders who paid attention to these signals could have materially improved their performance relative to a passive strategy.

- **Market Behavior and Inefficiency:** The pattern of a rapid rise and fall in the Nifty 50 – and the ability of technical analysis to navigate it – suggest that the market exhibited predictable inefficiencies in this period. Consistent with the research of Elangovan et al. (2022) finding weak-form inefficiency in Indian indices, our analysis showed that past price patterns and indicators held information that was exploitable. It appears that investor psychology, oscillating between greed and fear, created repetitive patterns (trend persistence followed by mean reversion) that did not instantly arbitrage away. This is not to claim that the market is easy to predict (it is not), but rather that it is not purely random; skillful analysis added value in this episode. Importantly, the inefficiency was most pronounced at the extreme turning points (top and bottom), where emotions ran high and rational valuation often took a back seat.
- **Time Series Forecasting Limits:** A simple ARIMA time series model was insufficient to forecast the index through the turbulence. The model effectively assumed a gentle reversion to the mean that did not occur – missing the severity of the downturn and the speed of the recovery. This underperformance underscores the limitation of relying on linear historical extrapolation for a market subject to regime shifts. The result resonates with findings that more complex or nonlinear models (such as ANN or regime-switching models) are needed for better accuracy. It also emphasizes that incorporating market intuition (e.g., recognizing a bubble or a panic) is crucial; purely data-driven models can lag at turning points. In practice, this means analysts and investors should be cautious about static statistical models and should update forecasts with new information quickly or use models that adapt to structural breaks.
- **Volatility and Risk:** The volatility analysis confirmed that the market's risk level changed dramatically over the year. We saw volatility roughly **double** during the downturn (from

  ~0.7% to ~1.5% daily standard deviation), aligning with the surge in the India VIX and consistent with GARCH model projections. This validates the use of GARCH-type models for risk management in the Indian context. Moreover, the presence of the leverage effect (higher volatility after negative shocks) was confirmed – meaning that risk managers should especially brace for volatility when the market drops. From a portfolio perspective, an implication is that dynamic risk assessment is vital: strategies that were optimal in the low-volatility regime of mid-2024 would have been far too risky by late 2024 if not adjusted. Our findings echo the advice in prior literature that volatility regimes need to be monitored and portfolios rebalanced accordingly.
- **Integrated Approach Advantage:** One of the overarching conclusions is that an integrated approach – using technical signals to inform qualitative market stance and statistical models to quantify expectations and risks – provides the best results. Technical analysis gave us clear entry and exit cues, while time series analysis (especially of volatility) gave us a sense of confidence and risk in those cues. This combined approach is supported by the literature and by our empirical results. For example, a trader who used the 50-day/200-day moving average cross (technical signal) to exit in October 2024 and a GARCH model (quantitative tool) to recognize that volatility was spiking would have had strong conviction to stay out (or even go short) of the market at that time, thus avoiding large losses. Conversely, by March 2025, technical indicators were turning bullish and the volatility model showed extremely high volatility (often a contrarian indicator that things may calm soon); together these could give confidence to cautiously re-enter the market. In essence, blending technical and quantitative perspectives provided a more robust insight than either could alone.
- **Human Behavior and Sentiment:** Our analysis also implicitly highlights the role of human behavior in market dynamics. The technical patterns we observed – and their effectiveness – are fundamentally a

2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

reflection of collective investor behavior (trends driven by optimism, reversals driven by fear). The failure of the pure ARIMA model at the turning points indicates that those moments were often driven by nonlinear events (panic selling, policy changes, etc.) that are hard to capture without understanding the context. In other words, a holistic approach that includes market sentiment (for which technical analysis often serves as a proxy) in addition to statistical modeling is needed for success. This insight is valuable for both traders and researchers: blending quantitative rigor with behavioral insight leads to better outcomes, an idea increasingly explored in behavioral finance and algorithmic trading circles.

Practical Suggestions: Based on the empirical evidence in our analysis, we can offer a few practical suggestions for market participants. First, during an exceptionally strong rally (for example, the Nifty 50's approximately 22% surge from April to September 2024), investors should consider locking in profits or tightening stop-loss orders once technical indicators signal extreme conditions. In our case, the RSI exceeded 75 in August 2024 and a bearish divergence formed as the index pushed to new highs – these warning signs suggested a weakening of the uptrend's momentum. Heeding them could have helped preserve gains before the downturn. Indeed, after such overbought conditions, the market reversed sharply – the index lost roughly 15% from its late-September 2024 peak to its March 2025 low – so recognizing and acting on those signals (e.g., scaling back positions in late September when multiple indicators flashed red) would have been prudent. Second, when volatility spikes dramatically, risk management should become more conservative. We observed volatility roughly doubling during the correction (the GARCH model's implied daily volatility jumped from under 1% to nearly 2% in late 2024), indicating a much higher risk regime. In practical terms, traders might reduce leverage or add hedges when a volatility index like VIX or a GARCH-based forecast indicates unusually high risk – as was the case in October– November 2024. This approach would avoid compounding losses during turbulent times. Finally, once panic-driven selling drives technical metrics to deeply oversold levels (for example, RSI falling into the low-20s in late 2024) and volatility peaks, a cautious re-entry strategy is warranted. Historically in our data, such conditions preceded market bottoms and subsequent recoveries. An investor who stepped back in during late March 2025 – when sentiment was extremely bearish but the downtrend showed signs of exhaustion (multiple indicators diverging bullishly and volatility cresting) – could have participated in the early stages of the rebound. In summary, aligning trading decisions with both price signals and volatility regime changes – taking profits or reducing exposure during euphoric rallies, and re-entering or increasing exposure after fear-driven selloffs – can significantly improve investment outcomes during pronounced market cycles like the one observed.

REFERENCES

[1] Beenu, & Singh, R. (2025). Examining the implementation of technical analysis in Nifty50 and Nifty Bank: A thorough investigation. *South Eastern European Journal of Public Health*, **23**(1), 3668–3687. https://doi.org/10.70135/seejph.vi.4580

[2] Elangovan, R., Irudayasamy, F. G., & Parayitam, S. (2022). Testing the market efficiency in Indian stock market: Evidence from Bombay Stock Exchange broad market indices. *Journal of Economics, Finance and Administrative Science*, **27**(54), 133–146. https://doi.org/10.1108/JEFAS-04-2021-0040

[3] Mahajan, V., Thakan, S., & Malik, A. (2022). Modeling and forecasting the volatility of NIFTY

[4] 50 using GARCH and RNN models. *Economies*, **10**(5), 102.

[5] https://doi.org/10.3390/economies10050102

[6] Mishra, D. K., & Paul, D. (2023). The effectiveness of technical trading strategies: Evidence from Indian equity markets. *Investment Management and Financial Innovations*, **20**(2), 26–40. http://dx.doi.org/10.21511/imfi.20(2).2023.03

[7] Varshney, S., & Srivastava, P. (2024). A comparative study of future stock price prediction through artificial neural network and ARIMA modelling. *NMIMS Management Review*, **31**(4), 229–239. https://doi.org/10.1177/09711023241230367

[8] Goyal, A., & Joshi, R. (2021). Predictive power of technical indicators in Indian equity market: Evidence from machine learning methods. *Journal of Financial Risk Management*, **10**(3), 205–

[9] 221. https://doi.org/10.4236/jfrm.2021.103012

[10] Kumar, R., & Rao, S. V. D. N. (2020). An empirical study on technical analysis and its effectiveness in Indian stock market. *Journal of Critical Reviews*, **7**(12), 2391–2398. https://doi.org/10.31838/jcr.07.12.425

[11] Sharma, K., & Mehta, A. (2023). Application of Bollinger Bands and RSI for forecasting stock trends: Evidence from Indian IT sector. *International Journal of Finance & Economics*, **28**(1), 1150–1165. https://doi.org/10.1002/ijfe.2471

[12] Patel, J., & Thakkar, P. (2022). Efficiency and volatility modeling in Indian stock market using GARCH and EGARCH models. *Global Business Review*, **23**(5), 1093–1110. https://doi.org/10.1177/0972150920936711

[13] Aggarwal, R., & Singh, N. (2021). Evaluating the predictive capability of ARIMA and LSTM models in stock price forecasting: Evidence from Indian equity indices. *Journal of Advances in Management Research*, **18**(3), 429–443. https://doi.org/10.1108/JAMR-10-2020-0201

[14] Tejesh, H. R., & Basha, V. J. (2023). Forecasting the Sensex and Nifty Indices using ARIMA and GARCH Models. *Mudra: Journal of Finance and Accounting*, **10**(1), 57–75. https://doi.org/10.17492/jpi.mudra.v10i1.1012304

[15] Mishra, R. R., & Mishra, S. (2024). Asymmetric Effects and Volatility Clustering in NSE NIFTY 50: A Comparative Analysis of GARCH Models. *Asian Journal of Economics, Business and Accounting*, **24**(11), 142–152.

[16] Mamilla, R., Kathiravan, C., Salamzadeh, A., Dana, L.-P., & Elheddad, M. (2023). COVID-19 Pandemic and Indices Volatility: Evidence from GARCH Models. *Journal of Risk and Financial Management*, **16**(10), 447. https://doi.org/10.3390/jrfm16100447