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Capture Market Trends through Multi-Indicator Confirmations using Reinforcement Learning Models

Rajraushan Kumar[1], Arup Kadia[2*], Suryansh Kumar[3], Aditya Sharma[4]

[1,3,4] Student, BCA (DS & AI), Faculty of Information Technology & Engineering, Gopal Narayan Singh University, India, Email: aadisharma04042005@gmail.com
[2] Assistant Professor, Faculty of Information Technology & Engineering, Gopal Narayan Singh University, India, Email: kadia.arup@gmail.com

Abstract
Trading on the stock market is a very complicated activity, and the main reasons for this are: high volatility, a lot of market noise, and changes in the behaviour of the investors, which are taking place at a very fast pace, and all these factors together are making the trading signals less reliable when the single technical indicators are used one by one. To solve these problems, the authors of this paper come up with a super resilient multi-indicator trading system that combines Simple Moving Average Crossover (SMAC) for trend detection with Average Traded Volume (ATV), Money Flow Index (MFI), and Put–Call Ratio (PCR) as supporting indicators. SMAC is the main method that provides buy and sell signals; at the same time, ATV approves market participation, MFI states the strength of both momentum and money flow, and PCR reflects the sentiment of the market, which is derived from the derivatives market. The new system is tested on large-cap stocks through considerable backtesting and using various time frames, which include short-term, medium-term, and long-term trading horizons. The evaluation is conducted with the help of important metrics like cumulative returns, trade accuracy, Sharpe ratio, and Sortino ratio. The experimental results show that the strategy of combining SMAC with ATV, MFI, and PCR has significantly surpassed the traditional SMAC-only methods, as it has reduced false signals, overtrading and risk-adjusted returns have been improved. One major point that the research has made is that by merging trend, volume, momentum, and sentiment data into a single trading model, a more reliable and understandable automated trading system is created, which is fit for the real-world market conditions.

Keywords: Simple Moving Average Crossover (SMAC), Average Traded Volume (ATV), Money Flow Index (MFI), Put–Call Ratio (PCR), Algorithmic Trading, Technical Indicators, Market Sentiment, Stock Market Analysis

1. Introduction

The trading of stocks in the market is a very complex process, and this is induced by factors such as serious fluctuations, unpredictable price movements, and unknown situations due to economic factors, liquidity changes, and the psychology of the investors. These conditions make it hard to create trading strategies that will always give a positive return. Technical analysis-based methods using traditional approaches are still very much used primarily for their simplicity and interpretability; however, they are often beaten in action through a dynamic market. Single-indicator strategies are, in particular, very susceptible to market noise, which in turn leads to frequent false signals, excessive trading, and unstable performance throughout different market phases.

Reinforcement learning (RL) technique has, in recent years, become one of the strongest methods in the field of algorithmic trading as it can very well model the process of sequential decision-making and eventually lead to the optimisation of rewards over a long time. Supervised learning methods are different in that the RL agent is allowed to continuously interact with the market environment whilst learning trading policies. Many researchers have asserted that trading systems based on RL can be superior to traditional rule-based ones when trained on historical data [1]. On the contrary, the data-driven RL models are purely based on price information only, and hence they are slow in their convergence, unstable, and hard to interpret, especially during a volatile market.

In an attempt to minimise the impact of these drawbacks, researchers have started to work on the combination of technical indicators and smart trading systems. The Simple Moving Average (SMA) crossover is among the most common trend-following approaches, mainly due to its simplicity, but at the same time, it is prone to giving such signals that are late or even mistaken in sideways or low-liquidity markets. Volume-related indicators such as Average Traded Volume (ATV) can facilitate the identification of the direction of the market, thus separating strong trends from minor price movements easily [2]. Another thing is the Money Flow Index (MFI), which is a combined representation of both price and volume; it signals the right time for sellers and buyers to enter the market through identifying the phases of buying and selling. The indicator of market sentiment derived from the derivatives data, especially the Put-Call Ratio (PCR), has a major contribution to the decision-making process by revealing the expectations of investors and the psychological biases in the market that are in favour of the buyers or the sellers.

With these remarks in mind, this paper presents a strong multi-indicator trading framework that creatively mixes Simple Moving Average Crossover (SMAC) with Average Traded Volume (ATV), Money Flow Index (MFI), and Put-Call Ratio (PCR). Each of the four indicators works together to determine the exact trend direction, strength of volume, behaviour of momentum, and sentiment in the market, which leads to fewer false signals and more reliable trading. The suggested method underwent a thorough assessment through extensive backtesting on large-cap stocks across short-term, medium-term, and long-term timeframes. The results of experiments indicate that the SMAC-ATV-MFI-PCR method has a constant edge over the traditional single-indicator approaches in terms of profitability, trade precision, and risk-adjusted returns [3].

2. Literature review

The merging of machine learning and reinforcement learning (RL) techniques has been the main reason that algorithmic trading has changed a lot. The traditional methods relied mainly on fixed technical rules and thus could not adjust to the rapidly changing and uncertain market environments. Recent publications point out the necessity of hybrid trading systems in which the technical indicators are combined with adaptive learning algorithms that will provide the system with more robust and accurate decisions. This literature review offers a comprehensive study of reinforcement learning-based trading systems, particularly focusing on the interplay of Simple Moving Average Crossover (SMAC), Average Traded Volume (ATV), Money Flow Index (MFI), and Put–Call Ratio (PCR) in the context of intelligent trading frameworks.

2.1.Reinforcement Learning in Financial Markets

The journey of reinforcement learning as a powerful concept for breaking up into sequential decision-making problems in the financial markets is the story of winning over the hard problems. The surveys of Dey et al., (2024).among others, summarise that the RL agents, as a result of their interaction with the market environment, can learn the optimal trading strategies instead of the traditional method of following the predefined rules. Besides, Yu et al. (2022) and Kadia et al. (2025) stress that RL is the best method to deal with non-stationary and uncertain market conditions. Despite that, the studies make the point of the challenges of instability, slow convergence, and limited interpretability in the application of deep reinforcement learning models contingent solely on raw price data. The mentioned limitations lead the researchers to the use of structured technical indicators as a means to enhance the stability and performance of the learning process.

2.2. Simple Moving Average Crossover Strategies

The Simple Moving Average (SMA) crossover strategy is still considered one of the best trend-following techniques in the field of technical analysis, mainly because of its ease of use and ability to effectively determine the market direction. Batten et al. (2014) proved that SMA-based strategies were very efficient in stock market trading, however, the regimes were also pointed out as a factor of their performance. Jha et al. (2025) claimed that the performance of traditional financial models could be significantly enhanced through optimization and adaptive techniques, thus suggesting that static SMA parameters might not be working well in a dynamic market. Kadia et al. (2025) conducted a study in which they found that the application of SMA-based trend detection along with reinforcement learning and confirmation indicators results in a considerable reduction of false signals, thereby validating the claim that SMAC is a key trend-identification component in intelligent trading systems.

2.3. Volume's Effect on Technical Trading

Volume-based indicators are among the most important factors in price confirmations as they show the strength of the prevailing market. Xiong et al. (2023) were successful in showing that machine learning models that took into account trading volume had better stock price prediction accuracy. Kamble and Patil (2023) came up with a volume-weighted reinforcement learning strategy and their results indicated decreased over-trading and increasing profitability. All the experiments mentioned above pointed to the impact that Average Traded Volume (ATV) has on detecting the strength of trends. Another thing that can help in confirming a trend besides volume is using momentum indicators based on both price and volume data, as this makes the signal more reliable. The Money Flow Index (MFI) indicates the phases of accumulation and distribution thus revealing the buying and selling pressure. The linking of ATV and MFI provides a strong filtering of weak signals and a bolstered trend-following strategy.

2.4. Sentiment Indicators and Put–Call Ratio (PCR)

The modern trading systems have made market sentiment a crucial part because it shows the investor's psychology beyond price and volume data. Sentiment-aware reinforcement learning models, as pointed out by Adhikary et al. (2025), show better flexibility under unstable market conditions. High Put-Call Ratio (PCR) values drawn from the derivatives market mean bearish expectations and low values indicate the opposite, therefore, bullish. Wu and He (2023) proved that adding sentiment indicators, like PCR, to the reinforcement learning model not only makes the trading more accurate but also lessens drawdowns. Thus, PCR functions as a reliable confirmation of sentiment when utilized along with other indicators such as trend, volume, and momentum.

2.5. Hybrid Models: Combining Technical Indicators and Reinforcement Learning

Recent studies have provided substantial evidence for the use of hybrid trading models that combine technical indicators with reinforcement learning algorithms. Li et al. (2021) found that reinforcement learning systems strengthened by indicators have a quicker convergence and superior risk-adjusted performance than price-only models. Xiong et al. (2023) showed that applying technical indicators in deep Q-learning brings about a notable increase in automated trading performance. Wu and He (2023) likewise demonstrated that multi-indicator fusion produces more stable policy learning and greater trading precision. Such findings reveal that hybrid models employing indicators like SMAC, ATV, MFI, and PCR offer a more informative and interpretable state representation for reinforcement learning agents.

2.6. Research Gaps and Opportunities

Reinforcement learning–based trading systems present different challenges that still have a long way to go in terms of research for one of the most exciting and attractive areas of AI (Dey et al. (2024). Fundamentally, only a very tiny number of studies exist that have either tried individual indicators or limited combinations of SMAC, ATV, MFI, and PCR all at once in integrated form within a unified PPO-based reinforcement learning framework. Even more than that, a good number of deep reinforcement learning models that are lack of interpretability and may be recognized only by their short-term performances are of little applicability in real-world situations (Karaila, 2024).

Proximal Policy Optimization (PPO), a method introduced by wang et al. (2022), not only guarantees stable but also efficient policy learning, making it a great candidate for financial trading scenarios. Nevertheless, this powerful algorithm has hardly been used in the area of multi-indicator trading models. The study, which addresses the above-mentioned issues, is proposing a PPO-based hybrid trading framework that seamlessly combines SMAC for trend detection, ATV for volume confirmation, MFI for momentum validation, and PCR for sentiment analysis, with the ultimate goal of creating a reliable, interpretable, and adaptive trading system that can cope with the real-world stock market conditions.

3. Methodology and model specifications

This research paper introduces a hybrid multi-indicator trading system that combines the use of classic technical indicators with the application of a Proximal Policy Optimization (PPO)–based reinforcement learning model to improve trading precision and trustworthiness. The system creates a combination of Simple Moving Average Crossover (SMAC) trend detection with the confirmation indicators of Average Traded Volume (ATV), Money Flow Index (MFI), and Put–Call Ratio (PCR). The complete process involves collecting data, computing indicators, validating signals, making decisions based on reinforcement learning, and evaluating performance.

3.1. Data Acquisition

The stock market figures have been derived from reliable and universally accepted financial sources. The data may be obtained from primary stock exchanges like the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) in India, the New York Stock Exchange (NYSE) in the USA, and all other worldwide exchanges. The dataset is comprised of Open, High, Low, Close, and Volume (OHLCV) data as well as the required derivatives data for the computation of the Put–Call Ratio.

The historical data are divided into training and test sets for the reinforcement learning model, while the real-time data are utilised for producing trading signals under live market conditions. In this study, the OHLCV of the selected large-cap stocks on the NSE for a period of five years are taken into consideration.

3.2. Data Processing

Financial time-series data may be incomplete as a result of weekends when the market is closed or for other reasons, like temporary shutdowns of trading activities. Missing values are filled through the forward-fill method to maintain continuity. The entire dataset is preserved to ensure that the chronological order, which is a prerequisite for the time-series learning process, is preserved. All the non-essential attributes are removed, and only features that are necessary for the calculation of indicators and the training of models are retained.

3.3. Calculation of Simple Moving Average Crossover (SMAC)

The Simple Moving Average (SMA) is the foremost indicator used in trend identification. The SMA offers the market's direction by averaging the prices over a given period, thus mitigating the influence of the daily price fluctuations.

$$\mathbf{SMA}(\mathbf{t},\mathbf{n}) = \frac{\mathbf{1}}{\mathbf{n}}\sum_{\mathbf{i}=\mathbf{0}}^{\mathbf{n}-\mathbf{1}} \mathbf{P}_{\mathbf{t}-\mathbf{i}} \qquad 1$$

where Pt is the closing price at time t, and n is the window length.

Two SMA values are computed:

- Short-term SMA
- Long-term SMA

Trading signals are generated as:

- **Golden Cross (Buy Signal):** Short-term SMA crosses above long-term SMA
- **Death Cross (Sell Signal):** Short-term SMA crosses below long-term SMA

SMAC indicator is capable of detecting market trends but it can lead to false signals in case of horizontal or low-liquidity markets, thus requiring support of other indicators.

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Figure 1: 12 Days and 26 Days SMA Crossover of HDFC Bank (1st June,2020 – 31st May,2025)

In Figure 1, the moving averages of 12 days and 26 days along with their crossovers are shown over the last 5 years. The 12-day SMA is marked in orange and the 26-day SMA is the green line. When the orange line crosses the green line from below to above, a golden crossover takes place and a buy signal is generated, which is indicated by the green triangle; on the other hand, the death crossover or sell signal is marked by the red triangle, which occurs when the orange line crosses the green line from above to below.

3.4. Average Traded Volume (ATV) Confirmation

To back up the SMAC signals, the Average Traded Volume (ATV) was utilized as an indicator of volume confirmation. ATV indicates the average number of shares that have been traded over a specific period and reflects the degree of market involvement.

$$ATV_t = \frac{1}{m}\sum_{i=0}^{m-1} V_{t-i} \qquad 2$$

where Vt represents trading volume at time t.

A SMAC signal is considered valid only if:

$$V_i > ATV_t \qquad 3$$

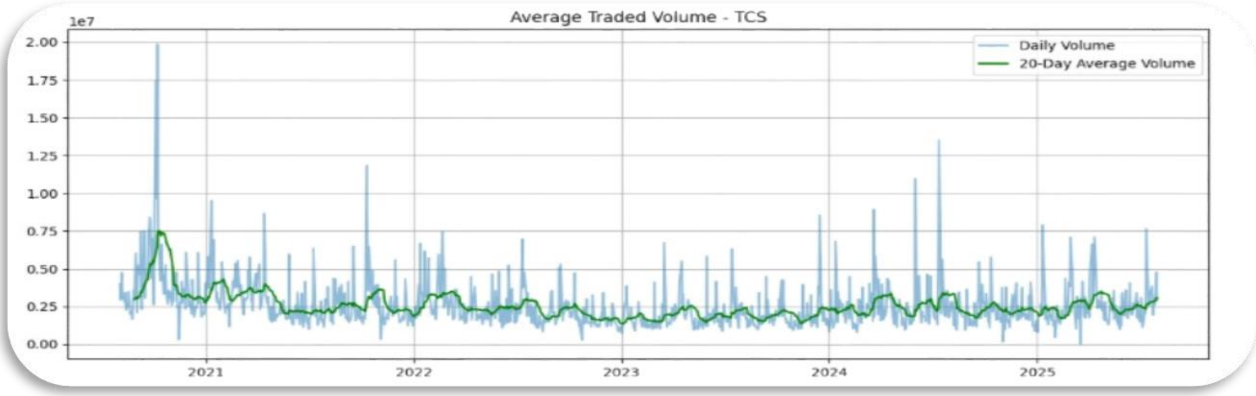

Figure 2: Average Traded Volume 20 Days MA (1st June,2020 – 31st May,2025)

As illustrated in Figure 2, trading volumes over the past five years are displayed alongside a 20-day moving average line of the same. The ascending lines indicate that traders are becoming more interested in the specific stock, resulting in an increase in volume. There is a strong likelihood of a significant price movement (either upwards or downwards) happening soon. The direction of the price movement is indicated by the SMA and MFI where the moving average line shows downtrend implying that the traders are losing their interest in the stock. There are high chances of sideways movement. To support this, a threshold medium was applied. Buy signals from SMA were only acted upon if ATVMF was above its 20-day mean, implying positive money inflow; sell signals were confirmed when ATVMF dropped below the mean.

3.5. Money Flow Index (MFI)

The Money Flow Index (MFI) is a momentum-based indicator that uses both price and volume to detect accumulation and distribution phases in the market. To calculate MFI, typical price and volume of trading are used over a specific period.

MFI values range between 0 and 100:

- **MFI < 20:** Oversold condition (supports buy signals)
- **MFI > 80:** Overbought condition (supports sell signals)

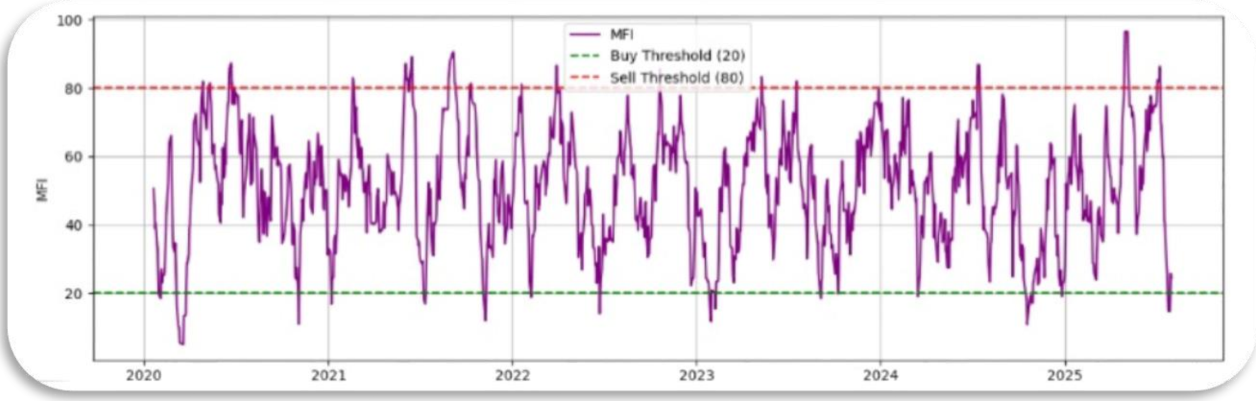

Figure 3: MFI indicator of Reliance Industries (1st June,2020 – 31st May,2025)

In Figure 3, the money flow indicator is shown. The two threshold lines at 20 and 80, respectively, denote oversold and overbought situations. A buy signal is confirmed by SMA when the price falls below 20, while a sell signal is confirmed by SMA when the price rises above 80.

MFI verifies the pattern of the SMAC signal by checking that the pressure is either buying or selling at the time.

3.6. Put–Call Ratio (PCR) Sentiment Analysis

The Put–Call Ratio (PCR) helps in determining the market sentiment by scrutinizing the derivatives market data. The ratio indicates the comparison between the aggregate open interest of put options and call options.

$$\text{PCR} = \frac{\text{Total Put Open Interest}}{\text{Total Call Open Interest}} \qquad 4$$

- **PCR > 1: Bearish sentiment**
- **PCR < 1: Bullish sentiment**

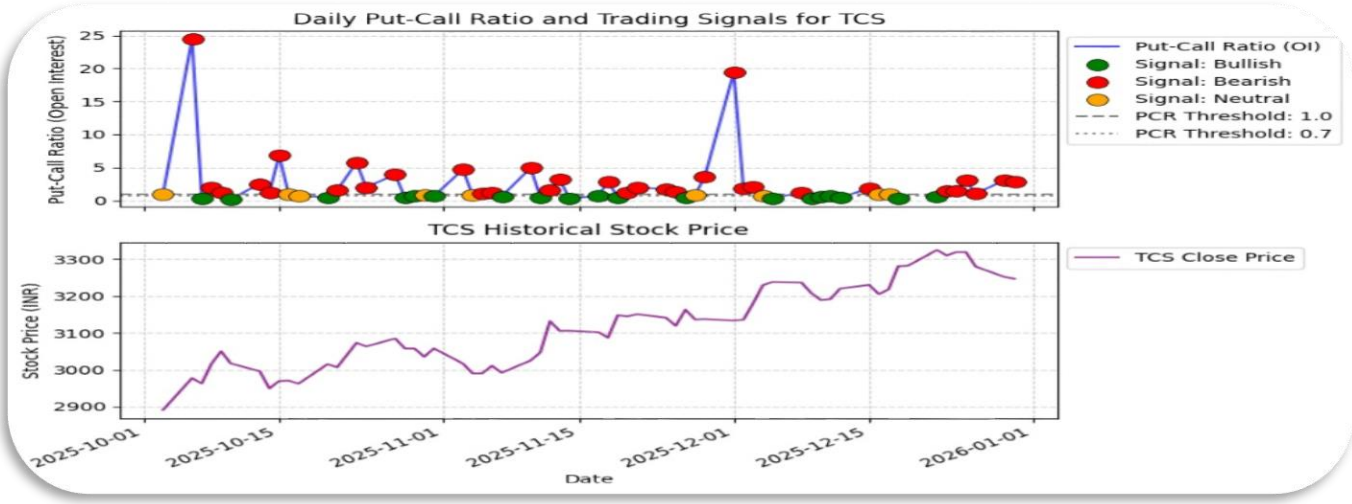

Figure 4. PCR based trading chart of TCS for 3 months

PCR confirms directional signals and discourages you from going against the market's mood.

3.7. Reinforcement Learning Using PPO

An example agent of reinforcement learned this framework using the PPO (Proximal Policy Optimization), in order to enhance its trade performance.

- **State Space:** SMAC signal, ATV confirmation, MFI value, PCR value, and position status
- **Action Space:** Buy, Sell, Hold
- **Reward Function:** Net profit adjusted for transaction costs and penalties for incorrect trades

The PPO objective function is given by:

$$L^{PPO}(\theta) = E[\min(r_t(\theta)A_t, \mathrm{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t] \qquad 5$$

where rt(θ) is the probability ratio, At is the advantage function, and ϵ is the clipping parameter.

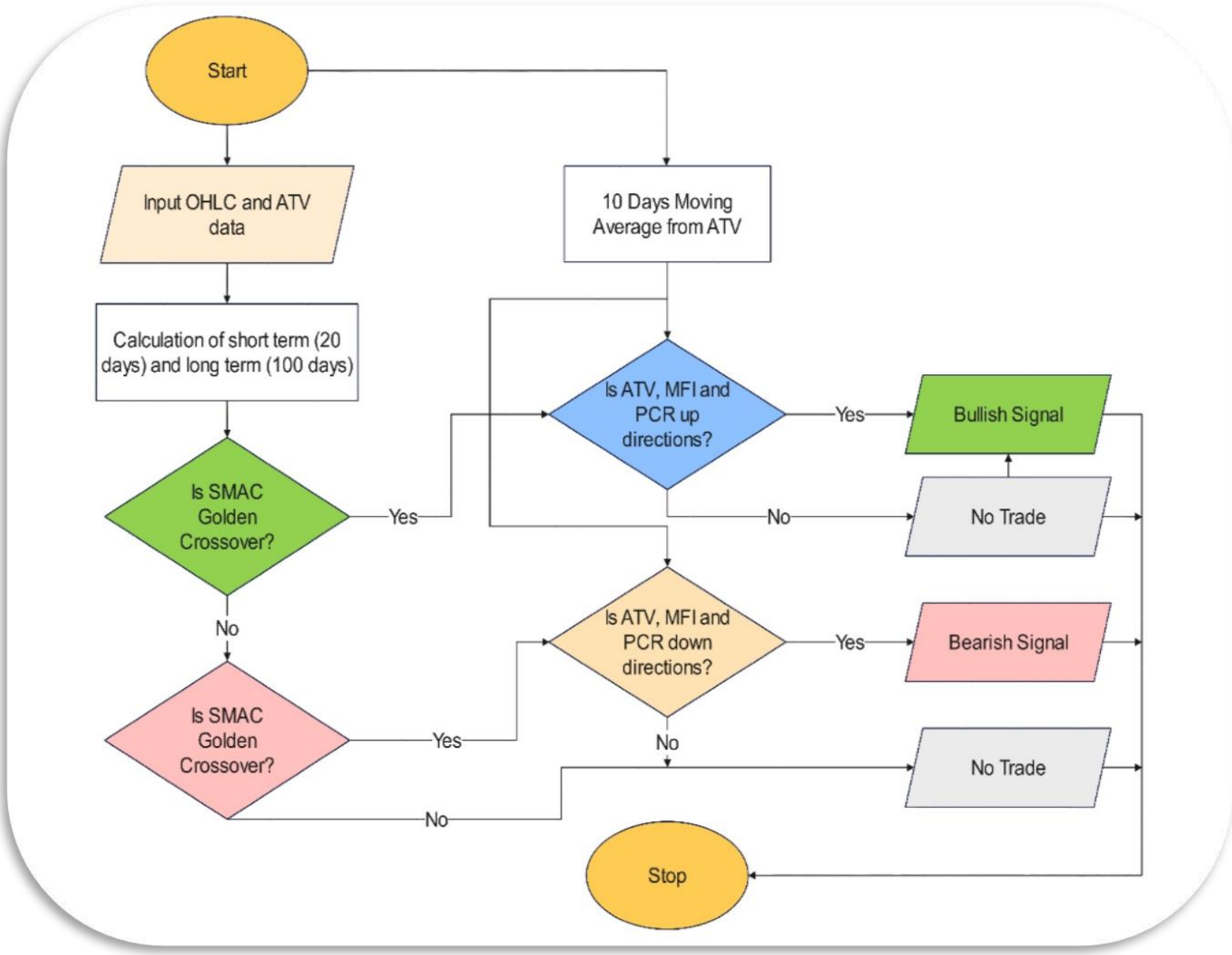

Figure 5: Flowchart of the proposed SMAC–ATV-MFI–PCR trading strategy

3.8. Summary of Methodology

The suggested approach unites SMAC for spotting trends, ATV for checking market participation, MFI for confirming momentum, and PCR for synchronizing sentiment. Thus, these indicators together present a well-organized and easy-to-interpret state to a PPO-based reinforcement learning agent which gains the ability to trade optimally by learning from the past market interactions. This mixture of methods surprisingly minimizes the occurrence of wrong signals to the point that they stay within the limits of overtrading and at the same time trading performance with regard to risk and return gets better in the environment of real-world markets.

4. Empirical Result

The suggested SMAC–ATV–MFI–PCR trading system, which was fine-tuned employing a Proximal Policy Optimization (PPO)–based reinforcement learning model among others, was put to the test by the method of extensive backtesting on the historical data of the stock market. In this case, the experimental analysis aimed to find out how well the new method would work under different market conditions and over varied trading periods. The performance was measured not only against traditional SMAC strategies but also using the key evaluation metrics like cumulative returns, trade accuracy, Sharpe ratio, and Sortino ratio. These metrics together assess both profitability and risk-adjusted performance.

The experiments were performed with large-cap stocks in order to assure liquidity and the reliability of data. For the sake of robustness, the analysis was done in three timeframes: short-term (5-minute), medium-term (hourly), and long-term (daily).

4.1. Short-Term Performance (5-Minute Time Frame)

On a short-term basis, the SMAC-only strategy was responsible for numerous trades because of the frequent crossover signals, although the high market participation it created had its downside in the form of overtrading and a large number of false signals, especially in low-volume and range-bound market conditions. Therefore, the overall profitability and risk-adjusted performance were still inconsistent.

The filtering of trades by the Average Traded Volume (ATV) as a confirmation filter not only ensured that only the best trades got executed but also the most active market participation. The Money Flow Index (MFI) was then added to the process and it instantly doubled the power of quality control by making sure that buy and sell signals were always in sync with the market being either bullish or bearish. The Put–Call Ratio (PCR) also came into play as an additional filter that took the mood of the derivatives market into account, so no trades that went against the prevailing sentiment of the investors were allowed.

This way, the SMAC–ATV–MFI–PCR–PPO framework not only provided higher cumulative profits but also better trade accuracy and lower drawdowns when compared with the SMAC-only strategy in short-term trading.

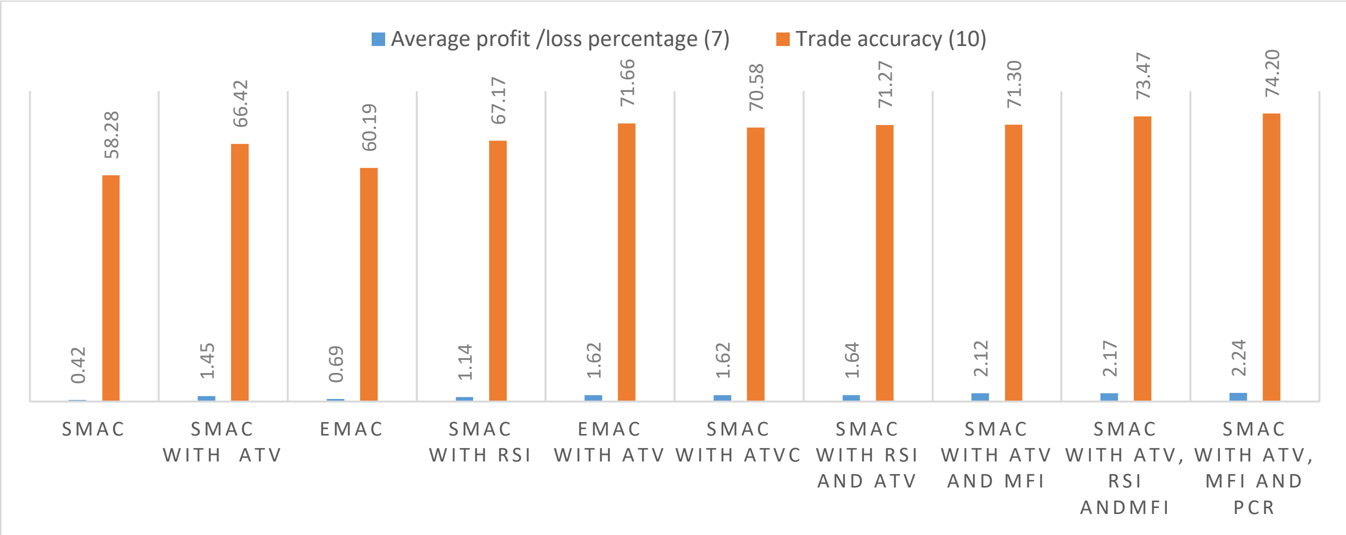

Figure 6: Cumulative profit and Trade accuracy are compared in 10 strategies in 1 month 5-min time frame

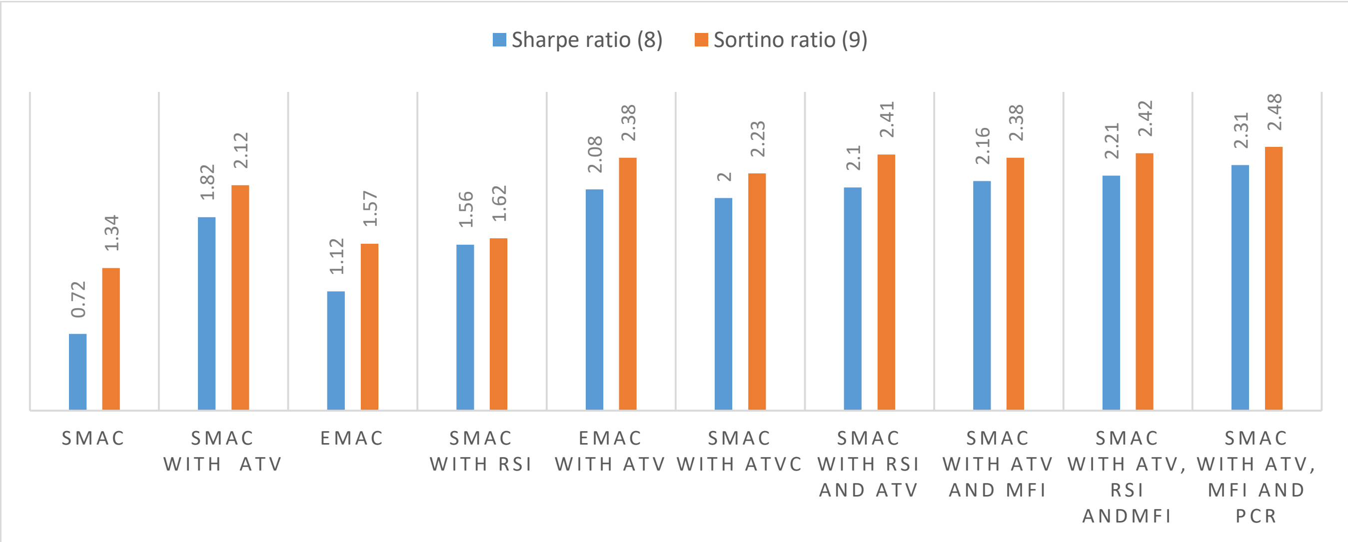

Figure 7: Sharpe ratio and Sortino ratio are compared in 10 strategies over 1 month 5-min time frame

4.2. Medium-Term Performance (Hourly Time Frame)

The medium-term evaluation based on hourly data over a one-year period proved the multi-indicator confirmation to be very effective. The SMAC-only strategy kept getting caught in sideways markets too often and therefore did not perform consistently due to the frequent false signals.

AVT use contributed to a very low number of unnecessary trades. The reason is that trades were only executed when there was sufficient liquidity to support them. MFI contributed to the validation of the momentum, while PCR ensured that the market outlook was in accordance with the sentiment of the market. A PPO-based reinforcement learning agent also helped by further optimising the timing of entry and exit through learning from the historical behaviour of the market.

To sum it all up, the proposed framework not only won over baseline strategies with respect to smoother equity growth, but also with regard to trade accuracy, Sharpe and Sortino ratios.

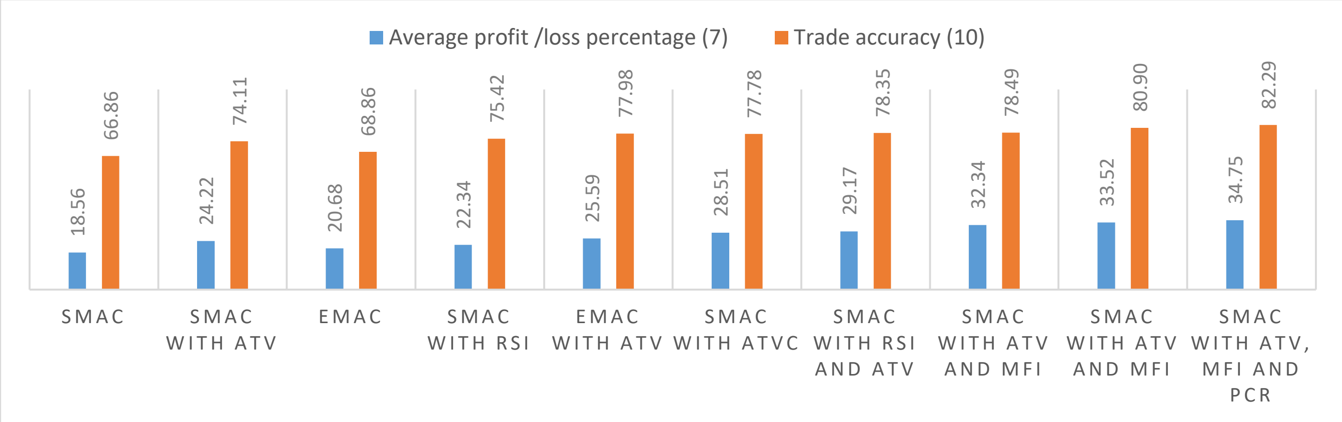

Figure 8: Cumulative profit and Trade accuracy are compared in 10 strategies in 1-year's hourly time frame

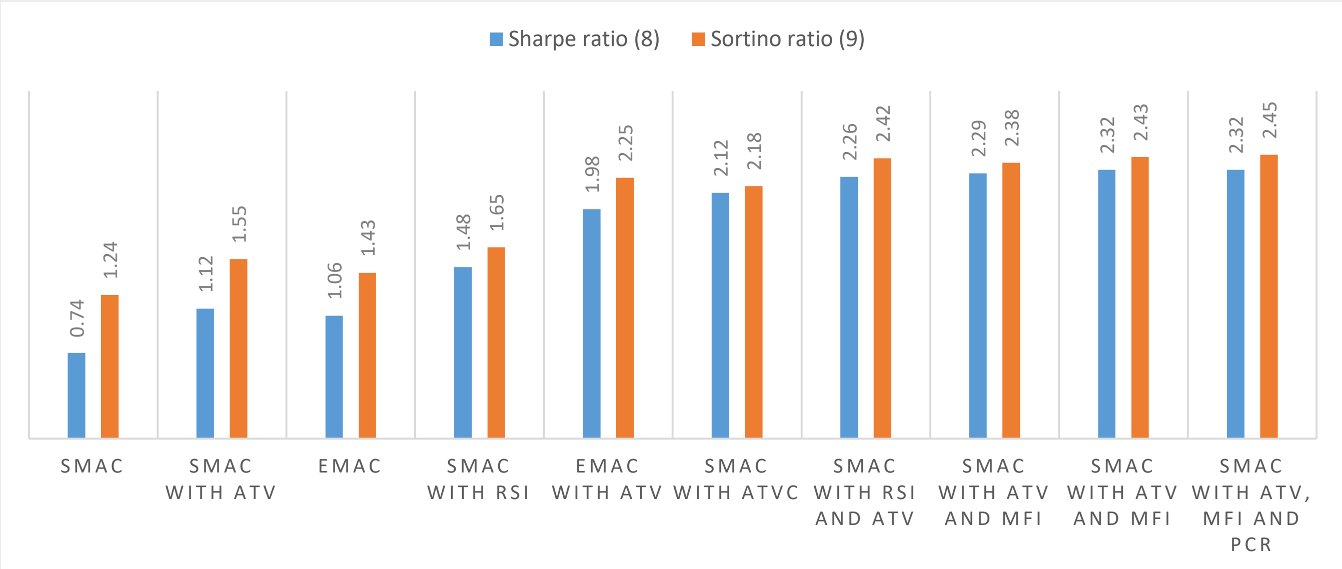

Figure 9: Sharpe ratio and Sortino ratio are compared in 10 strategies over 1-year hourly time frame

4.3. Long-Term Performance (Five-Year Period)

The long-term study, which lasted for five years, showed the proposed trading system's strength and stability. The SMAC-only method had erratic results because of the long periods of sideways movements and quick shifts in volatility.

On the other hand, the SMAC–ATV–MFI–PCR framework alongside PPO-based execution continuously filtered out weak signals and prevented misinterpretations driven by sentiment. ATV confirmed trend strength, MFI stopped late entries and exits, and PCR matched trades with long-term investor's expectations.

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The suggested strategy gave the highest total returns, higher trade accuracy, and the best risk-adjusted performance in comparison to other evaluated horizons.

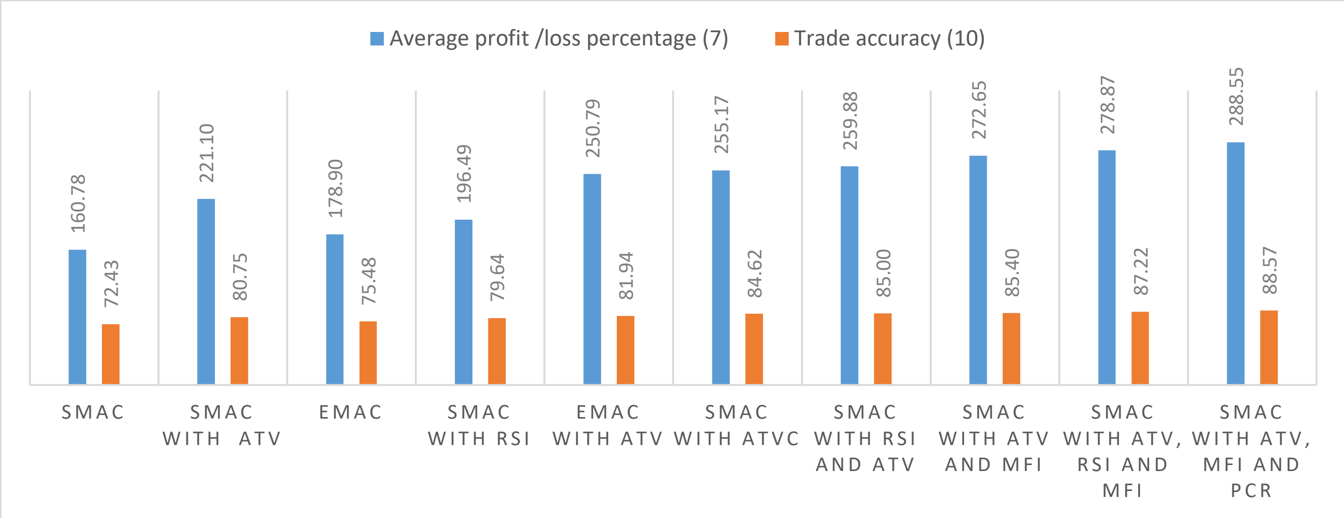

Figure 10: Cumulative profit and Trade accuracy are compared in 10 strategies in 5-years

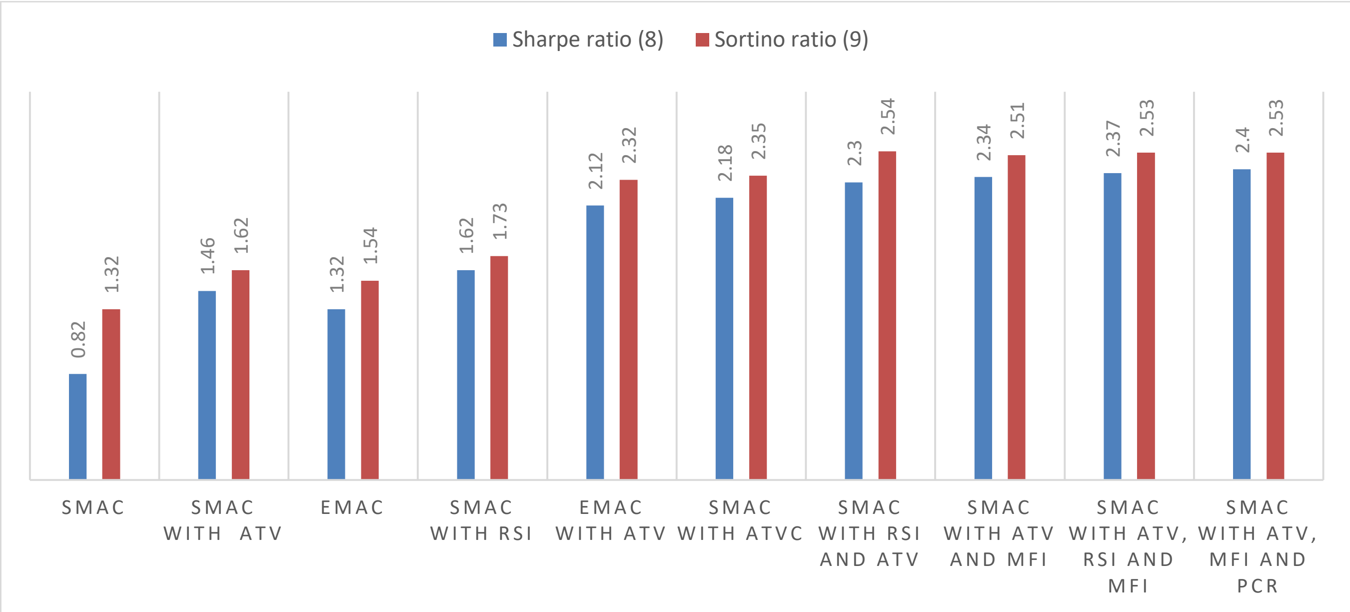

Figure 11: Sharpe ratio and Sortino ratio are compared in 10 strategies over 5-years

4.4 Overall Result Interpretation

The single-indicator strategy like SMAC has been the main focus of the investigation and the findings unambiguously support that it is not enough alone to cope with market noise and volatility. Allowing the use of MFI along with ATV, MFI provides momentum validation, and PCR brings in sentiment awareness through the integration of the methods. The PPO-based reinforcement learning agent has even more execution efficiency since it learns over time the optimal trading actions. The combined application of SMAC–ATV–MFI–PCR–PPO was always winning against the conventional techniques in terms of the profitability, accuracy of trades, and risk-adjusted returns, thus it was practical in automated trading applications in the real world.

5. Conclusion

The paper offered a strong multi-indicator stock trading framework that included the integration of Simple Moving Average Crossover (SMAC) with the Average Traded Volume (ATV), Money Flow Index (MFI), and Put–Call Ratio (PCR), optimized through a Proximal Policy Optimization (PPO)-based reinforcement learning model. The major aim of the proposed method was to increase the accuracy and reliability of trading by cutting down on false signals and overtrading which have become the characteristic of single-indicator strategies especially in the case of high volatility and low liquidity markets. The extensive backtesting results for the short, medium, and long trading horizons showed that although the traditional SMAC strategy is still very effective and it is mainly used for identifying the trend's overall direction, it is facing the problem of lagging and frequent misleading signals if only SMAC is used. The use of ATV as the volume confirmation indicator made sure that the price moves were backed up by already good market participation. Then, MFI made momentum stronger by detecting the accumulation and distribution phases thus holding off early or late trade execution. The role of PCR was to furnish a sentiment-based confirmation layer, which mimic trading decisions according to the prevailing investor outlook from the derivatives market. The PPO-based reinforcement learning agent allowed the trade execution to be further improved by its learning of the best buying, selling, and holding actions from past market interactions while also factoring in transaction costs and risk. The SMAC–ATV–MFI–PCR–PPO integrated framework invariably gave rise to greater cumulative returns, superior trade accuracy and better performance on a risk-adjusted basis than the traditional SMAC-based strategies.

In general, the outcomes validate that the combination of trend, volume, momentum, and sentiment indicators in a reinforcement learning system results in a more trustworthy, understandable, and flexible automated trading solution. Further studies may investigate the possibility of expanding the suggested framework to include multi-asset portfolios, the use of more sentiment sources, and performance assessment in real-time trading conditions.

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