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Enhancing market forecast accuracy: A structural equation model analysis of technical indicators in the Bank Nifty index

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ABSTRACT

The growing intricacy of international financial markets requires sophisticated approaches to managing investments and minimizing losses. This paper evaluates the use of Structural Equation Modeling (SEM) to improve forecast accuracy by integrating multiple technical indicators within the Bank Nifty Index. The study employs SEM to estimate the effect of key technical indicators such as the Simple Moving Average (SMA), Relative Strength Index (RSI), Volume Weighted Average Price (VWAP), and Moving Average Convergence Divergence (MACD) on trading volumes and closing values. The model considers both direct and indirect relationships among these indicators to determine their overall impact. The study highlights the significance of certain technical indicators in predicting market trends. It demonstrates SEM's effectiveness in estimating interrelationships among these indicators and formulating predictive models. This study underscores SEM's effectiveness in financial forecasting by showing that incorporating multiple technical indicators enhances prediction accuracy and improves decision-making in financial markets. Investors and traders can use these findings to develop better trading strategies, improve market stability, and maximize returns. This analysis supports the case for a multi-indicator approach in forecasting models.

Contribution/ Originality: This study uniquely applies Structural Equation Modeling (SEM) to examine the relationships among multiple technical indicators within the Bank Nifty Index, enhancing market prediction accuracy. Unlike previous research, it integrates SMA, RSI, VWAP, and MACD to assess both direct and indirect impacts, providing a comprehensive predictive model for improved trading decisions.

1. INTRODUCTION

Effective market forecasting is key to growing the financial markets like India. The Nifty Bank Index, made up of prime banking shares of India, is an important barometer of industry health, and it helps in making investment decisions (Bhatia & Gupta, 2020; Sehgal & Gupta, 2021). Technical analysis indicators such as the Simple Moving Average (SMA) and Relative Strength Index (RSI) are useful in predicting price and volume movements of whole stocks within periods (Kuo & Chou, 2021; Mitchell, Białkowski, & Tompaidis, 2020; Srivastava, Zhang, & Eachempati, 2021; Zatwarnicki, Zatwarnicki, & Stolarski, 2023).

This indicator helps to fine-tune the timing of trades and trading with other signals in the markets. How they have performed in the past is dependent on a variety of economic and market variables. Studies such as Agrawal, Shukla, Nair, Nayyar, and Masud (2022) discourage aggressive banks from making aggressive predictions compared to when adopting high-tech measures that emphasize the necessity. See also Bustos and Pomares-Quimbaya (2020) and Singh and Khushi (2021). More sophisticated measures in technical analysis have forced confidence levels to higher margins, documenting that lower risks mean more investments. Evolutionary deep learning models, in particular, which integrate multiple indicators, have reported good successes (Agrawal et al., 2022).

According to Liu and Pan (2020), the integration of indicators in volatility forecasting ranges improves forecasting capability and demonstrates the importance of technical analysis of the market for making future predictions. Their results reveal that typical economic indicators are overshadowed by technical indicators in a typical economy; therefore, technical indicators are important for complete investment strategies. Among these are the Moving Average, the Moving Average Convergence Divergence, and the Relative Strength Index, which are crucial for stock trend analysis (Srivastava et al., 2021; Wang, Ho, & Li, 2020). In addition, Structural Equation Modeling is embraced to express the evolutionary nature of market participants and the different levels of volatility in the market, thus improving the integrity and predictive power of a financial model (Gong & Lin, 2021; Luo, Demirer, Gupta, & Ji, 2022; Xuan & Kim, 2020). The growing reliance on simple technical indicators highlights an evolution into complex trading strategies and reaffirms the role of technical analysis in complex financial markets.

Existing literature suggests that the forecasting ability of technical indicators of the Bank Nifty Index can be enhanced through SEM techniques. Unfortunately, there exists a vacuum of research in this area of interest. Most existing studies have focused primarily on a select few indicators like moving averages and trading volumes while missing other indicators that could offer a richer understanding of market behavior and trends (Ayala, García-Torres, Noguera, Gómez-Vela, & Divina, 2021; Liu & Pan, 2020; Manjunath, Marimuthu, & Ghosh, 2023; Yang, Wang, & Li, 2022). Few researchers focus on the movement of the market, which permits the exclusion of crucial elements.

Also, the Bank Nifty index continues to be analyzed through unique prisms. Avenues of thought that remain untapped tend to degrade the use and reliability of the outcomes. Presently, the construction of structural equation models does not incorporate all the required constructs, measures, and indicators, for example, SMAs, RSI, and MACDs, in conjunction with variables such as stock trading volume and closing prices (Falke, Schröder, & Endres, 2020). These issues reflect serious gaps in the currently prevailing models and frameworks.

Furthermore, methodologies that combine technical indicators with sentiment analysis, such as those derived from news or social media, have not been explored in depth. This absence creates uncertainty surrounding the operation and accuracy of specific technical indicators on their own (Yang et al., 2022). As such, this disconnect in analysis has stunted the progress of strong validation models that could significantly improve the quality of predictions regarding the performance of technical indicators.

It is notable in literature that there is little focus given to mediation in SEM estimations, which in most contexts has remained indirect, especially in finance. This gap highlights the complicated multiway relationships that exist between technical indicators and the movement of markets (Cho et al., 2023). There is also a relative deficiency in the use of some advanced SEM methods of confounding, such as bootstrapping, in financial modeling. It has been demonstrated that the inclusion of bootstrapping techniques improves the credibility and precision of market dynamics evaluations by decreasing estimation deviation and strengthening accuracy (Brandt, Umbach, Kelava, & Bollen, 2020).

Such prospective benefits notwithstanding, there is scant evidence that indicates any fine-tuning or real-world use of SEM models to improve the fit indices in relation to the Bank Nifty Index. For financial models to be structurally sound, one of the prerequisites is for them to meet certain SEM fit indices, but such allowance in the existing literature is limited (Savalei, 2021). Moreover, there is an extremely limited body of literature that examines the structural validity as well as the forecasting ability of constructs of SEM in financial markets, specifically for the

Bank Nifty Index. This absence in the literature corresponds to a very important gap identified by Garnier-Villarreal and Jorgensen (2020) and calls for more research to be conducted.

These gaps present a clear direction for future study focused on enhancing SEM procedures in finance. The creation of specific SEM tactics designed to improve the predictive ability and structural integrity of financial models would greatly aid in understanding and predicting intricate market activities, such as those exhibited by traditional banks.

The objective of this study is threefold. First, it addresses the problem of achieving accuracy in using technical indicators for the banking sector in the emerging market, which results in less precise predictions about the market and less effective investment strategies. Second, the relative ineffectiveness of such indicators for the Nifty Bank Index tends to exacerbate the chances of staggering losses (Yıldırım, Toroslu, & Fiore, 2021). Literature, however, tends to focus such analyses on case studies, often on these measures 'stand-alone', considering how these measures work in the banking sector. Owing to this gap, there is an increasing demand to build a model specifically aimed at the stocks of Indian banks, which would help improve forecasting accuracy (Li, Wu, & Wang, 2020).

Existing practices do at times make use of a handful of technical indicators, which invariably may compromise the predictive efficacy of the forecasted variables (Alsubaie, El Hindi, & Alsalman, 2019). Although recent attempts to incorporate Triple Exponential Moving Average (TEMA) and MACD indicators by machine learning algorithms for technical analysis have not been suitable because those indicators do not cover all aspects of market activities, such limitations impair their predicting abilities (Alsubaie et al., 2019; Ayala et al., 2021). In contrast, a non-linear model of the Chinese stock market that we applied, which is built around a wider spread of indicators, appears to offer greater accuracy and reliability in predictive forecasting. This suggests that the use of such techniques could also be relevant within the context of the Indian banking industry (Alfonso & Ramirez, 2020). It is necessary to develop models that not only include a variety of technical indicators but are also adjusted to the particularities of developing countries. These models would increase the precision as well as the reliability of the forecasts for stock pricing and combine with forecasts of the markets to assist in the formulation of sound investment strategies tailored to cope with the complex interactions of Indian banking stocks.

The primary contributions of this paper are the following: a) to analyze the reliability of selected technical indicators (SMA, RSI, VWAP, PVT, ATR, CCI, Bollinger Bands, Stochastic Oscillator, and MACD) in estimating the trading volumes and closing values of the Bank Nifty Index. As part of this, this research used SEM to identify the strongest predictors that permit the achievement of the objective of this study. b) to analyze the net effect that specific technical indicators have on market behavior, through SEM's evaluation of coefficients of structural equations. With this analysis, we will be able to measure the influence of these indicators concerning the trading volume and daily closing values of the Bank Nifty Index. c) this objective has attempted to quantify and statistically test the said impacts, which would enhance the present knowledge base in relation to forecasting market trends in empirical finance. d) this objective has sought to assess the indirect effects and mediation mechanisms advanced with the use of the SEM framework. To that end, the aim is to find out and quantify the effects of those technical indicators on the daily closing values of the Bank Nifty Index through trading volumes. The study will employ sophisticated bootstrapping techniques to disentangle the intricate interactions among these variables to unravel their effects on market outcomes.

In this study, stock market players will be exposed to the use of technical indicators such as the Simple Moving Average (SMA), Relative Strength Index (RSI), and Volume Weighted Average Price (VWAP). Structural Equation Modeling (SEM) will be used to forecast the Bank Nifty Index. The study investigates the extent to which these indicators can anticipate trading volumes and closing prices and the role they play, both directly and indirectly, in market dynamics. Additionally, the systemic architecture of the SEM framework and its predictive capabilities will be examined. This study seeks to conduct a comprehensive investigation to enhance the indicators in making strategic trading decisions, which would contribute to the empirical finance literature and practical financial analytics. Using

Structural Equation Modeling (SEM), the Bank Nifty Index may be forecasted using SMA, RSI, and VWAP. The investigation explores the predictive abilities of these indicators concerning trading volumes and closing prices, as well as their interrelationships and feedback effects on market structure. The SEM framework's structural makeup and its predictive variables will also be evaluated. This extensive investigation will enable the indicators to establish strategic trading decisions, thereby enhancing the literature in the field of empirical finance and the practice of financial analytics.

This research paper consists of six main parts. The first part of the research, referred to as the Introduction, explains the aim and significance of the research work. The next part, Theoretical Framework and Hypotheses Development, explains a few technical indicators including Simple Moving Average (SMA), Relative Strength Index (RSI), Volume Weighted Average Price (VWAP), Price Volume Trend (PVT), Average True Range (ATR), Commodity Channel Index (CCI), Bollinger Bands, Stochastic Oscillator (K), and lastly, Moving Average Convergence Divergence (MACD). The third part of the paper, Methodology, describes the data, including sampling processes for the research and the method of investigation. The fourth part of the research, Results and Discussions, presents the results, including models' explanation of fit, quality indices, structure loading, composite reliability, average variance extracted, Cronbach's alpha, full collinearity, discriminant validity, as well as path coefficients and significance levels of these measures. Part 5 is titled 'Conclusion and Implications of the Study.' It summarizes the most substantial findings of the study and examines their broader implications. Finally, section 6 acknowledges the limitations of the research and proposes various avenues for future research.

2. REVIEW OF LITERATURE AND HYPOTHESES DEVELOPMENT

2.1. Simple Moving Average (SMA)

The Simple Moving Average (SMA) is considered one of the basic functional devices for making financial analyses. It is computed as the average of a loaf of bread from yesterday, today, and some other time tomorrow. This process enhances the average because the oldest price is replaced with the newest price, thereby creating a clearer view of the price chart. This improves the ability to detect trends during the day when prices fluctuate.

$$SMA(n) = n1\sum i = 1nPi$$

Where:

n is the number of periods for the moving average.

Pi is the price at period i, while the summation $\sum i{=}1nPi$ is the aggregation of the prices at period 1 to n

1 n is the figure which determines the mean value of the sum of number of prices.

The Simple Moving Average (SMA) is important for gauging the movements within the stock market, as it provides traders with useful information when deciding what course of action to take next. Kouaissah, Orlandini, Ortobelli, and Tichý (2020) also noted that the SMA's ability to show market direction is related to the stock price and the SMA's moving average price. If the stock price is above the SMA, the trend is bullish; if the stock price is below the SMA, the trend is bearish.

That said, while these observations demonstrate the usefulness of SMA, they rest on the assumption of steady trend movements, which may indeed not be the case in erratic markets, and there exists a possibility of the SMA needing supporting instruments to determine movement trends. In addition, SMAs might also serve as dynamic support and resistance lines, hence forming possible zones for going long or going short. According to Jiang, Jia, Chen, and Chen (2022), prices usually bounce back at widely accepted key SMA levels, which traders consider important. This perspective emphasizes the need to consider SMA levels in decision-making. Nonetheless, their practicality may be rendered useless in periods of erratic market conditions – which is a major limitation of SMAs viewed from multiple perspectives.

Algorithmic trading practices spawn enormous gains from SMA's crossover trading techniques, where a buy signal is generated by a short-term SMA that crosses above a long-term SMA, while the opposite provides a sell signal (Ayala et al., 2021). This method is beneficial, albeit systematic, as it presumes static conditions of the market, which do not take into consideration external factors such as news or macroeconomic events that can disturb technical patterns. These signals may be impressively more dependable with the addition of extra indicators. The combination of SMAs with machine learning is believed to be beneficial in attaining this goal. Kuo and Chou (2021) asserted that the augmentation of SMAs with more complex algorithms aids in the prediction of varying degrees of volatility depicted in the short and long-term SMAs by the difference of the two. Nevertheless, the deployment of these hybrid models in practice poses one of the greatest challenges in terms of needed computational power and mastery, which is a hindrance for individual traders and small companies alike.

In the time series forecasting models, SMAs assist in the determination of price time series by smoothing them out and not distorting them, thereby improving predictability (Moeini Najafabadi, Bijari, & Khashei, 2020). The question of how to respond smartly to sudden price changes while using SMAs, and at the same time being able to strengthen the development of robust financial models, is one of the issues that creates concern. The creation of an optimized configuration of SMA should lead to a more reliable model. SMAs also aid in the implementation of automated trading strategies, as users can program a buying and selling timeline that maximizes profits and minimizes losses (Kulshreshtha, 2020). This is beneficial as it increases productivity, but it poses a danger because undue dependence on past prices, which don't always predict future prices, is risky. This drawback can be addressed by using live data and sentiment analysis. Finally, SMAs enable the development of hybrid systems that integrate technical analysis and trading query systems (Jeong, Lee, Nam, & Oh, 2021). These semi-automated systems are a testament to the power of SMAs in improving the technical aspects of the analyses. The problem, however, is that the models built around these hybrid systems depend on certain parameters that must be consistently updated to meet the demands of changing markets.

This thorough examination summarizes the contributions and flaws in the current research on SMAs, proving the lack of an integrative approach that combines SMAs with other necessary tools and techniques. These findings support the development of the hypothesis and point out the need for additional pragmatic testing in fluctuating market conditions.

H_{a1}: The daily trading volumes of the Bank NIFTY Index are affected by the SMAs of heavyweight banking stocks.

H_{b2}: The heavy-weight banking stocks' SMAs have an impact on the closing values of the Bank NIFTY Index.

2.2. Relative Strength Index (RSI)

Technical analysis uses the Relative Strength Index (RSI), a momentum oscillator, to gauge the speed and size of price movements in a particular direction. It assists traders in recognizing when assets, such as stocks, have reached extreme levels of buying or selling, with the goal of predicting possible changes in the price direction.

$$RSI = -\{\frac{100}{1+R}\}$$

Where:

RS denotes the rate of average losses for the time frame covered and gains obtained during the same period.

The Relative Strength Index, or RSI, is one of the most widely used and acclaimed technical indicators that measure overbought and oversold market conditions. An RSI value of 70 or more implies that an asset is overbought and there is a potential for values to drop, while a figure below 30 indicates oversold conditions and hints at an imminent price increase (Zhu, Duan, & Jun, 2019). Although this method provides guidance for market entry and exit, timing effectiveness is not consistent across varying factors of the market or between asset classes, presenting potential limitations for its global use. Rather than simply forecasting market price shifts, RSI depends on and adjusts for trading volumes. Many traders waver in their strategies at RSI thresholds. Such adjustments could have radical consequences on stock prices due to the importance of trading volume on price movement (Naik & Mohan, 2021). This dependence explains why RSI is simultaneously viewed as a price or volume indicator, as its effectiveness is contingent on the characteristics of the market and the actions of other traders.

The effectiveness of RSI strategies differs among various markets. In the case of India, its relevance is still inconclusive. Even though some research contends that RSI increases portfolio returns and efficiency (Kulshrestha & Srivastava, 2020), there are reports of neutral results, suggesting that RSI strategies are not always profitable (Nor & Zawawi, 2019). These findings support the assumption that the effectiveness of an RSI strategy depends to a large extent on sensitive market conditions, timing, and the context of the trade.

The challenge with these seemingly contradictory pieces of research can be the underlying divergence in market structures. In many Asian stock markets, it has been revealed that roughly a dozen companies have taken advantage of RSI trading strategies as opposed to the traditional buy-and-hold model (Coe & Laosethakul, 2021). However, one must remain cautious when overgeneralizing because such companies are likely to be in markets with lower liquidity, higher volatility, and lightly constrained regulatory environments. Such an environment is not common in many regions. While some passively managed investment strategies are statistically more profitable than others, there are moments when relying solely on RSI is not ideal. Muruganandan (2020) demonstrated that for certain time periods, a passive buy-and-hold strategy would have yielded more favorable risk-adjusted returns. Such passive strategies are easier to execute as one does not require constant monitoring of the stock market. Over the years, this has been useful for investors looking to allocate their capital with minimal effort.

The global pandemic, especially in currencies such as Bitcoin, put to the test that RSI can prove beneficial even in circumstances where equities are at risk. There are even studies suggesting that, for countries like Russia, equities combined with other trading metrics such as the Chaikin oscillator were profitable (Zatwarnicki et al., 2023). Moreover, RSI has been used to detect irregularities such as stock market bubbles and even to forecast possible economic recessions (Naik & Mohan, 2021). This application further illustrates its greater usefulness compared to standard trading strategies, addressing issues of market volatility and systemic risk. However, unlike other aspects, its predictive ability in these contexts is not absolute and depends on the market as well as its economic conditions. Based on this critical evaluation, the following hypotheses were developed. The aim of the hypotheses is to fill the gaps that were identified in RSI literature and to enhance the understanding of its usefulness, as well as its application in other market environments.

H_{a3}: The RSI of heavyweight banking stocks influences the daily volume levels of the Bank NIFTY Index.

H_{b4}: The RSI of heavyweight banking stocks influences the daily closing values of the Bank NIFTY index.

2.3. Volume Weighted Average Price (VWAP)

VWAP is a trading benchmark utilized by investors and analysts to ascertain the mean price at which a stock has been traded during a day, considering both the volume and price.

$$VWAP = (\sum Price \times Volume)/\sum \text{Volume}$$

Where:

Price is defined as the value of a security at the time of each transaction.

Volume is defined as the number of shares exchanged in each transaction.

The summation ($\sum$) is taken over every trading transaction made from the beginning to the end of the day.

The Volume-Weighted Average Price (VWAP) has emerged as a popular trading strategy as it considers the price and the volume within a specified range. This information moves about and provides decent intelligence on both price changes and cash market activity, and for this reason, VWAP is heavily relied upon by traders and analysts. As cited by Mitchell et al. (2020), static models are considered superior to dynamic models, proving that the most important factor for improving trading strategies is the maintenance of the VWAP. While their studies shed light on effective ways of improving market modeling using static models, the question that arises is whether those models are appropriate and sufficient in changing market environments.

Biological modeling can be employed to refine intraday trade execution, which involves using the VWAP economy. This was shown by Jeong et al. (2021), whose approach has been found to increase the execution efficiency of trades while also offering additional support to overall market efficiency. With their findings, it becomes clearer that even though their study successfully applies the principle of VWAP in intraday trading, its use in different situations remains to be properly investigated. However, regarding the favoring of price stabilization during hours of market closure, it seems that VWAP has taken the lead (Frei & Mitra, 2021).

This leads to an increase in trust in the market as it provides a better closing price; yet, it also shows the risks of relying too much on the VWAP contracts during periods of price volatility, where there is low predictability of price stabilization. In their paper, Alexakis, Pappas, and Skarmeas (2021) stressed the importance of VWAP in regulatory and supervisory frameworks for its instrumental role in containing market abuse within Europe. In doing so, they studied the impact of VWAP on the pricing policies of electric car charging stations and how sensitive consumers were to prices by zone and time. This application across diverse economies indicates a multidisciplinary approach to VWAP, but its application across other unorthodox industries still lacks research.

Duffie and Dworczak (2021) predicted the success of VWAP in controlling price manipulation with regard to its confidentiality within stressed markets. Such findings indicate a promise in compliance with regulations and assistance during a crisis. However, further analysis is required to determine how much damage can be done when a market is extremely disrupted. Alfonso, Carnerero, Ramirez, and Alamo (2021) and Luo, Shi, Zhou, and Li (2021) reviewed the use of VWAP for institutional liquidation and large trade order optimization. VWAP has been shown to minimize market impact and maximize the likelihood of execution for orders in a specific period, as indicated in their studies.

Even though these studies positively commend VWAP for its efficiency in some respects, its reliance on volume data does raise some eyebrows about the low volume market's mispricing. All these findings put together have previously tracked the effectiveness of the VWAP moving average indicator towards improving trading strategies, achieving price controls and compliance, and developing economic applications in different industries. However, these benchmarks put forth and contextual constraints mapped out in these studies indicate that additional verifiable work is indeed needed to improve capitalism using the VWAP as well as to ameliorate the existing issues with it. The subsequent hypotheses that seek the more potent ramifications and utilizations of trading with MVWAP and market analysis have been crafted based on this synthesis.

H_{a5}: The banking stocks' VWAP influences the daily volume levels of the Bank NIFTY Index.

H_{b6}: The banking stocks' VWAP influences the daily closing levels of the Bank NIFTY Index.

2.4. Pivot Point (PVT)

The PVT indicator is a fundamental component of technical analysis, offering crucial insights into market patterns and possible reversal points by computing support and resistance levels based on previous price data.

$$PP = (High + Low + Close)/3$$

Where: High represents the maximum price that the stock reached during the last trade.

Low is the minimum price to which the stock dropped in the last trading session.

Close is the price equal to the average that the stock was selling for at the end of the previous session.

The Price-Volume Trend (PVT) analysis is a helpful method to devise sophisticated trading approaches as well as control risks associated with an investment over a prolonged period. It has already been shown through several analyses to converge towards better market prediction and higher profits. For example, Support Vector Machines (SVM) have been incorporated with PVT to increase the predictive ability of trading systems, which leads to improved trading results and profits (Kumbhare, Kolhe, Dani, Fandade, & Theng, 2023).

It alludes to the ability of the PVT methodology in the refinement of algorithmic trading systems, but its performance in different market conditions needs to be evaluated further. For example, Subathra (2021) used PVTs to forecast the market and evaluate price changes within the context of the competitive online trading market. The work illustrates the versatility of PVT in ever-changing trading conditions. On the other hand, the issue of being too dependent on historical data raises the question of how responsive it would be in times of abrupt changes in the market, which means that real-time indicators would be useful to have.

Kasparinsky (2022) pointed out that the integration of the PVT analysis perspective broadens further with the addition of Dow Theory, Elliott waves, and Fibonacci retracement levels. This set of rules helps in detecting the direction and changes of the market, which is useful for long-term planning in business. Ballová (2020) supports this view and focuses on PVT for the proactive analysis of the market. However, these blended techniques still require some work when it comes to effectiveness in a volatile or less liquid market. The PVT-based financial volatility network indicators introduced by Lee, Cho, Kwon, and Sohn (2019) display remarkable productivity during market chaos. While this discovery proves the cash flow PVT's strength during unstable periods, its stability in changing market conditions is still an aspect that requires further research to confirm its versatility.

Market anomalies like January have also been associated with the wide application of PVT in the financial analysis of Branch, Ma, and Orland (2018). This correlation consolidates the potential power of PVT in tackling the prevailing irregularities of the market. However, how effective PVT will be in improving the inefficiencies in different markets is still a question. The incorporation of PVT into MRI systems has contributed to improved management of financial distress risk, according to Figini, Maggi, and Uberti (2020). This same finding illustrates the power of PVT in promoting financial strength and control over risks. Nonetheless, the degree to which these advantages are gained in other financial systems and industries still needs to be investigated. Nti, Adekoya, and Weyori (2020) studied the suspiciously excessive monopolistic PVT trading systems and their systematic economic review roles. This overdependence on PVT raises concerns since its reliance on PVT continues; monolithic utilization of PVT analytical derivatives may lead to other inefficiencies.

These studies confirm the earlier claims that PVT is beneficial in forex trading, risk management, and enhanced strategy formulation. Nonetheless, the limitations and contextual constraints mentioned above call for more exploration so that the applications of PVT across different markets would be effective. These insights serve as a hallmark for formulating the next hypothesis.

H_{a7}: The banking stocks' PVT influences the daily volume levels of the Bank NIFTY Index.

H_{b8}: The banking stocks' PVT influences the daily closing values of the Bank NIFTY Index.

2.5. Average True Range (ATR)

The True Range (ATR) Indicator is a useful tool for measuring the volatility of stocks, commodities, and Forex, as long as price direction is not considered. The true range, which is measured by ATR, is the highest value of the differences between the current highest and lowest prices, the last closing price, and the highest and lowest prices. The normalized moving average, which serves the purpose of measuring volatility, is determined by taking the average of this number over a period of fourteen days.

$$TR = \max\left(Hight - \text{Low}t, | \text{Hight} - \text{Close}t - 1 |, \text{Low}t - \text{Close}t - 1\right)$$

$$ATR = \frac{I}{N}\sum_{t-1}^{N} TR\,\text{i}$$

Where: TRiTRi is the true range for the ii-th period.

Average True Range (ATR) is often used in the analysis of a company's stock to measure the volatility of the stock and assist in forecasting. In their study on estimating Value at Risk and Expected Shortfall for equities and indices, Meng and Taylor (2020) used ATR with intraday range data.

The results further demonstrate that ATR is an effective tool for quantitative risk assessments, thus becoming part of the more intensive trading risk analyses. Nonetheless, while there are many examples demonstrating ATR's effectiveness in these models, its use in calmer, low-volatility, or low-liquidity markets remains to be studied. In the case of the global economic downturn and COVID-19, Choi (2021) was among those who noted ATR's volatility versatility. Such versatility has been shown to be useful even in the most extreme changes in market conditions, thus making it an important measure for volatility in unknown circumstances. That said, its reliance on past data renders it incapable of forecasting unforeseen events in the markets. This indicates that there may be a need for real-time data to be incorporated.

ATR has been claimed to be used with further advanced methods of computation. For example, Zhou, Zhou, Yang, and Yang (2019) integrated ATR into a model that incorporated empirical mode decomposition with neural networks to bolster stock market trend predictions. In a similar manner, Ribeiro, Santos, Mariani, and dos Santos Coelho (2021) have also used ATR with echo state networks for stock price return volatility estimates. These studies indicate the merit of ATR in improving hybrid analytical models; however, the intricacy of such systems may be an issue for mass adoption. In the area of feature selection, Patel, Valderrama, and Yadav (2022) found that ATR incorporation in deep neural networks could improve stock market predictions. This application underlines the importance of ATR in predicting highly volatile markets.

Alotaibi (2021) also utilized volatility measurements with ATR in ensemble techniques to further demonstrate its Expected Conditional Variance (ECW) implications on the Saudi stock market models, which proved the enhancement of prediction model accuracy. These findings illustrate the potential of ATR technology to be applied to multiple markets, but its model-specific parameters may need further attention. Karaca, Zhang, and Muhammad (2020) investigated the use of ATR in high-frequency trading systems and defined thresholds for greater market sensitivity. Their study demonstrates how ATR is indispensable in modern trading approaches, as it provides traders with an edge in volatile markets. On the other hand, its reliance on high-frequency data may not be suitable for markets with slow trading activity.

In summary, the application of ATR for risk assessment, crisis market analysis, or even predictive models is multifaceted, emphasizing its importance in today's financial analysis. It has become an important component in complex trading strategies because it can assess volatility without regard to price movement. Despite its wide range of applicability, its limitations under specific market conditions and its computational constraints provide avenues for further improvement and development. This is the basis for formulating the theories that follow.

H_{a9}: The ATR indicator of heavyweight banking stocks influences the daily volume levels of the Bank NIFTY index.

H_{b10}: The ATR indicator of heavyweight banking stocks influences the daily closing values of the Bank NIFTY index.

2.6. The Commodity Channel Index (CCI)

Many traders use the CCI to identify commodities and stock cyclical movements. It detects overbought and oversold conditions by measuring price deviations from the statistical mean. How computations are done: First, the average of the high, low, and close prices is determined to find the Typical Price for each period.

$$TP = \frac{\text{High} + \text{Low} + \text{Close}}{3}$$

Secondly, the SMA of the Typical Prices (TP) for the last NN periods are calculated.

$$SMA - TP = \frac{1}{N}\sum_{i-1}^{N} TPi$$

Thirdly the mean deviation of each period's TP and the SMA are calculated.

$$\text{Mean Deviation} = \frac{\text{I}}{\text{N}} \sum_{i-1}^{N} \mid TPi - SMA - TP \mid$$

Finally, the CCI is calculated using the following formula:

$$CCI = \frac{TP - \text{SMA} - \text{TP}}{(0.015X\ Mean\ deviation)}$$

The constant 0.015 is used to ensure that approximately 70% to 80% of the CCI values fall between -100 and +100, under the assumption of a normal distribution of price movements.

The Commodity Channel Index (CCI) is a valuable technical indicator that has demonstrated significant utility in predicting market trends and improving financial analysis. Liang, Ma, Li, and Li (2020) confirmed CCI's ability to anticipate stock market volatility through the analysis of commodity prices in dynamic markets. This highlights CCI's role in bridging the gap between commodity price movements and equity market behavior, although its effectiveness may vary under extreme market conditions, warranting further empirical validation. Jeong et al. (2021) explored the integration of CCI with genetic algorithms, demonstrating its effectiveness in improving intraday trading volume estimates. This collaboration between traditional indicators and modern computational methods illustrates the potential of hybrid systems, though the complexity of such integrations may limit their accessibility to smaller market participants.

The combination of CCI with artificial neural networks (ANNs) has proven useful for stock price prediction and the development of comprehensive assessment models, as established by Chang, Wang, and Chuang (2021). Similarly, Chen et al. (2021) demonstrated how CCI enhances the inputs for advanced deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, significantly improving prediction accuracy. However, the computational demands and expertise required for these approaches suggest that their broader applicability may depend on further simplification and cost reduction.

Market mood indicators, when used alongside CCI, enhance the ability to understand market dynamics and predict investor behavior (Zhang, Chu, & Shen, 2021). This integration highlights the value of combining technical indicators with sentiment analysis, though the reliability of mood indicators in rapidly changing markets may pose challenges. Alkhatib, Khazaleh, Alkhazaleh, Alsoud, and Abualigah (2022) further emphasized CCI's utility in deep neural networks, specifically for forecasting adjusted close prices in equity markets. These findings underscore CCI's adaptability in refining financial forecasting models, though its dependence on high-quality input data necessitates robust preprocessing mechanisms. Vancsura, Tatay, and Bareith (2023) reinforced the value of CCI by showcasing its effectiveness in speculative transactions, particularly when combined with relative strength index strategies, further demonstrating its versatility in diverse trading scenarios.

Delis, Degiannakis, and Giannopoulos (2023) expanded on these findings, showing that CCI not only impacts market volatility but also influences price variations and enhances financial forecasting accuracy. These insights underscore the broader applicability of CCI in market analysis; yet, its performance in less liquid or emerging markets remains an area for further exploration. Ke, Zuominyang, Qiumei, and Yin (2023) highlighted CCI's ability to counter automated mini-gain strategies in stock trading, illustrating its practical application in defeating algorithmic trading inefficiencies. Bildirici, Şahin Onat, and Ersin (2023) demonstrated how integrating CCI with complex financial models improves the precision of market predictions, further validating its role in modern financial analysis.

The diverse applications of CCI—from hybrid computational models to market behavior predictions—highlight its importance in financial forecasting and market assessment. While CCI has proven to increase prediction reliability across various trading paradigms, its limitations in adapting to extreme market conditions and its computational complexity suggest areas for further refinement. These observations underpin the development of innovative financial strategies and support the adoption of CCI in advanced financial models.

H_{a11}: The CCI indicator of heavyweight banking stocks influences the daily volume levels of the Bank NIFTY index.

H_{b12}: The CCI indicator of heavyweight banking stocks influences the daily closing values of the Bank NIFTY index.

2.7. Bollinger Bands

Technical analysis uses Bollinger Bands to measure market volatility by deviating from SMAs. A central SMA with two dynamic bands signals overbought or oversold situations based on price volatility. The center band calculates the SMA of closing prices over the past N periods, while the standard deviation measures price dispersion for volatility and market sentiment analysis.

$$MB = \mathrm{SMA}N = \frac{1}{N}\sum_{i-1}^{N} Closei$$

$$\sigma = N1i = 1\sum N(\mathrm{Close}i - \mathrm{SMA}N)2$$

The upper and lower bands are calculated by adding and subtracting a specified number of k times the standard deviation from the middle band. Typically, k is set to 2, which adjusts the bands to cover approximately 95% of the data points, assuming a normal distribution.

Bollinger Bands are important in strategic trading because they help find unusual price movements when compared to moving averages, which could mean a change or continuation in trends (Chen, Lai, Hung, & Hong, 2022). Because they monitor market volatility, traders can pivot their strategies efficiently with the help of Bollinger Bands. When the bands widen, volatility and trend shifts are expected to increase, while narrowing bands highlight the opposite (Cohen, 2022). Although it is known that they are helpful, it is important to understand that Bollinger Bands alone do not possess sufficient sufficiency, and thus it becomes necessary to combine them with other analytic approaches to build a strong trade plan.

The use of machine learning approaches has improved the application of Bollinger Bands in automated trading systems. According to Cohen (2022), signals generated from Bollinger Bands are more accurate than those from ordinary systems. Furthermore, as demonstrated by Vergura (2020), replacing SMAs with EMAs increases responsiveness in the market and improves trend analysis. With these changes, it is evident that the trading environment continues to evolve, and these adjustments allow Bollinger Bands to remain relevant; however, the need for accuracy in the data input is crucial.

Fikri, Moussaid, Rida, El Omri, and Abghour (2022) argue that there was an increase in the reliability of trade signals in Forex transactions when integrating neural network-based systems with Bollinger Bands. Similarly, Xue, Ling, and Tian (2022) used a dual-layer Long Short-Term Memory (LSTM) model to improve portfolio management strategies in the cryptocurrency market, demonstrating its utility in multiple instruments. In the NIFTY50 market, Mittal and Nagpal (2022) showed that stock price prediction accuracy and decision-making were improved with the use of machine learning algorithms with Bollinger Bands.

Furthermore, Bollinger Bands have gained relevance in a myriad of economic situations rather than just trading. Ananthi and Vijayakumar (2021) used them in regression models to obtain signals for actual trading, while Sharif, Aloui, and Yarovaya (2020) tried to understand how Bands can be used to analyze stock performance amidst political and economic volatility. These studies highlight the many contexts in which Bollinger Bands can be used and their ability to adapt to market complexity.

Bollinger Bands are still relevant today based on how effective they are in all manners of financial analyses. They remain at the forefront of technical analysis today by increasing the precision of automated trades to help traders gauge market conditions in times of economic crises. The precision of these trading scenarios also enables the use of additional strategies. Given the above dynamics, the following hypothesis is set forth.

H_{a13}: The banking stocks' Bollinger Bands levels influence the daily volume levels of the Bank NIFTY Index.

H_{a14}: The banking stocks' Bollinger band levels influence the daily closing values of the Bank NIFTY Index.

2.8. The Stochastic Oscillator (K)

The stochastic oscillator K analysis attempts to find the turning points of the market by comparing the closing price of a security with the highest and lowest levels attained by the security price during the specified time. Alternatively, increasing the time or applying a moving average results in reducing the responsiveness of the oscillator to market changes. The Stochastic Oscillator is often presented as %K, the principal line, and %D, its average line.

$$\%K = \frac{Close - \mathrm{Ln}}{\mathrm{Hn} - \mathrm{Ln}} \times 100$$

Where: Close is the most recent closing price.

Ln: The lowest price.

Hn: The highest price over the last N periods.

With its capacity to forecast probable changes in prices and fluctuations in financial markets, the Stochastic Oscillator has emerged as an interesting way to manage the risk of investment and improve trading strategies. Risk management is assisted by providing estimations of market price volatility and stock price movements, and its use has been demonstrated by Nabipour, Nayyeri, Jabani, Shahab, and Mosavi (2020). While these stock price forecasts appear to be very useful, their accuracy is determined by the sophistication of the data sets and the methods employed, thus reinforcing the need to develop application frameworks to make it useful as intended.

Another noteworthy use of the Stochastic Oscillator is for output forecasting in multi-factor models. Shang and Zheng (2021) established its role in forecasting stock return expectations derived from SV-MIDAS modeling, both in-sample and out-of-sample predictions. This capability does improve market analysis since risk and return estimations become more accurate. Moreover, He et al. (2022) pointed out that the oscillator can also be used for optimizing investment strategies through enhanced diversification by carefully chosen sets of stocks in stochastic models to minimize loss. It is crucial in any investment because it helps form portfolios that are likely to meet the set risks and rewards.

Equally important in relation to the tolerance and biases of investors are stochastic models that Padhi and Padhy (2021) use to demonstrate the mechanisms that govern investor behavior patterns, which provide insight into market psychology and how it affects day trading. Zhang (2021) elaborated on these theoretical considerations by contouring stochastic factors as structural variables, which were mathematically modeled within the context of the stock market using structural equations. This method of modeling the stock market accentuates the great importance of stochastic modeling for any theory that seeks to explain the displayed randomness of changes in price and trading results.

The position of the Stochastic Oscillator is that it can be used not only in the stock markets but also in all other emerging markets, such as cryptocurrencies. According to Gil-Alana, Abakah, and Rojo (2020), it can be useful in controlling the stochasticity associated with the cryptocurrency market, which is characterized by highly volatile changes. This also serves to further confirm the indicator's usefulness for various other classes of assets and types of markets.

Because the Stochastic Oscillator is helpful for forecasting volatility and returns, portfolio allocation, and even behavioral finance, it is a crucial tool for modern financial analysis and forecasting. Such value is, however, not easy to come by in practice and is highly dependent on setting the proper parameters and combining it with other instruments to solve a given problem in a specific market. These observations are the basis for discussing the remaining theories that are going to be examined, demonstrating the effectiveness and applicability of the oscillator in diverse economic situations.

H_{a15}: The banking stocks' Stochastic oscillator (K) influences the daily volume levels of the Bank NIFTY Index.

H_{a16}: The banking stocks' Stochastic oscillator (K) influences the daily closing levels of the Bank NIFTY Index.

2.9 Moving Average Convergence and Divergence (MACD)

As a highly flexible trading tool, the Moving Average Convergence Divergence (MACD) can be applied to form new creative trading strategies. Agudelo Aguirre, Duque Méndez, and Rojas Medina (2021) demonstrate that a hybrid approach using MACD developed buy and sell signals through genetic algorithms, which, in turn, proved helpful to Agudelo Aguirre et al. (2021) in enhancing investment returns. According to Ayala et al. (2021), they also proved that the application of algorithms increases the precision of trading signals. This is particularly important in nations like India, where more aggressive order routing has yielded increased levels of profitability. The importance of using MACD in conjunction with deep learning techniques was exhibited by Srivastava et al. (2021), where the predictive power of the models within the Indian economic landscape increased relative specificity.

The application of MACD through deep learning techniques significantly enhances prediction accuracy, illustrating its performance alongside the advancement of technology. Neural networks have proven to be the most valuable structures for the development of MACD, as they aid in recognizing and internalizing intricate market trends. Khandelwal et al. (2023) demonstrate how regression models and machine learning models incorporating MACD have improved the accuracy of stock price predictions. This underscores the increased dependence on placing orders through automated systems, which is a result of a more sophisticated algorithmic trading environment. Khandelwal et al. (2023) also evaluated the high-frequency use of MACD and concluded that when used with a directional prediction model, the simulation results for the futures markets were more accurate. These results further support the hypothesis of MACD usage for different strategies within a developed trading environment.

Now, the sophistication of MACD's convergence with ultra-sophisticated technologies epitomizes intelligent assisted systems. It combines traditional indicators with cutting-edge computing tools, which make MACD adaptable and usable for different markets and asset classes without friction. This change imbues a deeper investment in algorithms depending on systems for the future of trading. MACD's broad-ranging applications have established its place as an important tool in contemporary financial analysis. Integrating this currency with postmodern technologies presents great opportunities for innovation - from increasing forecasting precision to facilitating trading on microsecond intervals. This discovery provides the basis for developing subsequent assumptions, which are structured for investigating the comprehensive consequences and use of MACD.

H_{a17}: The banking stocks' MACD influences the daily volume levels of the Bank NIFTY Index.

H_{a18}: The banking stocks' MACD influences the daily closing levels of the Bank NIFTY Index.

3. METHODOLOGY

3.1. Data and Sampling Description

The research centers around the four banks that contribute the most to the Bank Nifty Index, specifically looking at how changes in the index are impacted by them. The sector's largest constituents are HDFC Bank, which has a weightage in the index of 29%, ICICI Bank, which has a weightage of 23.73%, State Bank of India (SBI), which has a weightage of 9.14%, and Axis Bank, with a weightage of 9.19%. Addressing these banks, selected because of their importance in determining the direction of the index, provides valuable insights into the influence that large banking institutions have on the market indices and, therefore, the overall economy.

The choice of the sample period, variables, and the technique to be employed was made with specific focus on achieving the goals set for the research and covering the market in totality. The sample period of 507 trading days from February 2, 2022, to March 14, 2024, was selected to enable data collection across diverse market conditions encompassing both volatility and stability, thereby strengthening the findings. The selection of HDFC Bank, ICICI Bank, SBI, and Axis Bank was justified by the significant aggregate weight they contribute to the Nifty Bank Index and their importance in determining index level and overall market performance. These banks account for more than seventy percent of the index, which makes this index reasonably good at reflecting the movements in the industry. The variables selected were based on well-known technical indicators of the market like SMA, RSI, VWAP, and

MACD, due to their evident market predictions in literature and the need to comprehend market actions. Structural Equation Modeling (SEM) has been used in this research, which enables a multifaceted investigation of the correlations between these variables, distinguishing the direct and indirect effects caused. This solution not only adds value to the model's explanatory power but also guarantees that the results of the study are valid and can be double-checked for consistency with methodological practice.

As found by Jobst, Bader, and Moshagen (2023), a well-provided sample size is one aspect that ensures the reliability of the structural equation modeling (SEM) analysis. To provide sample size provisions in the WarpPLS software, the sample sizes using Inverse Square Root and Gamma Exponential techniques were determined to be 160 and 146 samples, respectively, to enhance adequate statistical power. These calculations assist in estimating the orders of sample sizes that could induce robustness in the model. The first figure presents a sample size of 160 that achieves a statistical power of approximately 0.8015. On the other hand, the second graph, which employs the gamma-exponential technique, requires up to 146 for a similar power, resulting in an assay level of 0.8005. The key parameters that measured the path coefficients included the path coefficient threshold, which was set at 0.197, a significance level of 0.050, and a target power level of 0.800. The data set included all trading days from February 2, 2022, to March 14, 2024, which constituted a total of 507 days. This period was sufficiently longer than the minimum requirement, which therefore increased the credibility of the findings that resulted from this study. The study made use of data on technical indicators, volume, and closing prices.

3.2 Research Design

To examine the relationship between the critical technical indicators, trading quantities, and the Nifty Bank Index daily closing price, this study employed Structural Equation Modeling (SEM). This approach is supported in the literature, as studies conducted by Herwartz and Xu (2022); Wang, Liu, and Wu (2020) and Zhang and Cai (2021) point out that SEM can be useful when exploring relationships among investor attention, market volatility, and trading volumes. Additionally, such models can capture the nuances in both quantitative and qualitative categories of data because the harmonized model of technical indicators and sentiment analysis enhances the forecasting capability of our stock price predicting model (Mohanty, Parida, & Khuntia, 2021). Besides the aforementioned theory, SMA, RSI, VWAP, PVT, ATR, CCI, Bollinger Bands, Stochastic Oscillator (K), and MACD were selected as technical indicators, since their effectiveness in predicting market directions has been evidenced in the financial sector (Ayala et al., 2021; Jeong et al., 2021; Mohanty et al., 2021). Considering the Nifty Bank index for the evaluation of dynamics in the Indian banking industry, it is worth mentioning that it includes the most liquid and well-capitalized banks in India (Rademaker, 2020).

To bring all data parts to equal measurement and to address some missing data points, normalization and mean imputation procedures were implemented in this case. This was done to allow for consistency in the conduct of time series analysis, as provided by Cho and Hwang (2023). Data that were in continuous closing value form were accordingly modified categorically for SEM analysis using the quantile-based discretization method. This method targeted the 25%, 50%, and 75% thresholds, dividing the data into a target of four known quartiles. Respondents were then assigned Likert scale levels with the values of the four levels. Q^1 valued responses denoted 'One' and were interpreted as 'Highly Negative,' with the rest being $Q_1 < x \leq Q_2$ for Negative, $Q_2 < x \leq Q_3$ for Positive, and $x > Q_3$ as Highly Positive. This classification was ideal since it succeeded in capturing the range and dispersion of values, which enhances the description of market dynamics (Alexopoulos et al., 2020; Lee & Kim, 2022; Schumacker & Lomax, 2004; Zhang, 2021).

This study implements structural equation modeling (SEM) methodology that comprises ten constructs, which consist of several technical indicators: Sparse Moving Average (SMA), Relative Strength Index (RSI), Volume Weighted Average Price (VWAP), Price Volume Trend (PVT), Average True Range (ATR), Commodity Channel Index (CCI), Bollinger Bands, Stochastic Oscillator, and Volume. Four reflective indicators of each construct, which are used during operationalization, make a total of 40 observable variables in the model. This arrangement allows for a succinct investigation of the direct and indirect relationships that these indicators have with the two measures of interest: the Bank Nifty index's trading volume and the trading day's closing values. It allows for the intertwining of multiple factors of relationship and how they act together, specifying direct effects and indirect mediation processes. Therefore, it adds to the understanding of the relevance of technical indicators to market outcomes. It is performed by estimating the path coefficients, thus ensuring there is statistical validity within the model. Since mediation mechanisms are not visible, examining indirect effects is important, and that is done using pathways in the SEM.

The first step in working with the data involves screening and cleaning the data for missing values and outliers. It was also checked for model reliability based on the measurement model, which utilized loading factors of more than 0.7. It was also verified whether composite reliability or Cronbach's alpha was used for construct reliability, and values were supposed to be more than 0.7. Construct validity was guaranteed by ensuring the average variance extracted was 0.5 or more. Cross-loadings were used to check the discriminatory construct validity. The path coefficients of these structural models were investigated to establish the relationships among the variables and their significance. The final fit of the structural equation model was assessed with several indices, namely the average path coefficient and the average R-squared. Multicollinearity of the estimates was assessed with the help of variance inflation factors. To validate the estimations of the model, bootstrapping was carried out.

4. RESULTS AND DISCUSSIONS

4.1. Evaluation of the Measurement Model

The evaluation of the measurement model in the context of Structural Equation Modeling (SEM) provides grounds for establishing the reliability and validity of the constructs contained in the model. This includes determining the sufficiency and correctness of the SEM, as well as the aggregate loading, composite reliability, average variance extracted, alpha coefficient, and full collinearity VIFs. The results and interpretation of the conclusions drawn from the measurement model evaluation are outlined.

4.1.1. Model Fit and Quality Indices

The fitness and quality of the model are assured according to the analysis results in Table 1. According to the analysis done by Roemer, Schuberth, and Henseler (2021), the Average R-squared is about 0.729 ($p<0.001$), which shows that the effect size is significant, explaining 72.9% of the unexplained variance in the dependent variables. The p-value less than 0.001 makes the AARS of 0.724 statistically valid, which enhances the reliability and predictive ability of the model. The Average Block Variance Inflation Factor (AVIF) of 1.994 and the Average Full Collinearity VIF (AFVIF) of 3.02 suggest minimal multicollinearity, and these results are supported by Chin et al. (2020). Like Dash and Paul (2021), Tenenhaus GoF at 0.706 shows outstanding predictive power, per (Falke et al., 2020). Model consistency is indicated by SPR at 0.947, RSCR at 0.999, and SSR at 1.00. Sharma, Liengaard, Hair, Sarstedt, and Ringle (2022) noted that the model's Nonlinear Bivariate Causality Direction Ratio (NLBCDR) at 1.00 shows its capacity to define complicated causal links. These measures demonstrate the SEM model's prediction accuracy, minimal multicollinearity, and robustness, validating its theoretical and practical contributions.

Table 1. Model fit and quality indices.

Model fit statistics	Recommended value	Actual value
Average R-squared (ARS)		0.729, P<0.001
Average adjusted R-squared (AARS)		0.724, P<0.001
Average block VIF (AVIF)	Acceptable if <= 5 ideally <= 3.3	1.994
Average full collinearity VIF (AFVIF)	Acceptable if <= 5 ideally <= 3.3	3.02
Tenenhaus GoF	Small >= 0.1, medium >= 0.25 large >= 0.36	0.706
Simpson's paradox ratio (SPR)	Acceptable if >= 0.7 ideally = 1	0.947
R-squared contribution ratio (RSCR)	Acceptable if >= 0.9 ideally = 1	0.999
Statistical suppression ratio (SSR)	Acceptable if >= 0.7	1.00
Nonlinear bivariate causality direction ratio (NLBCDR)	Acceptable if >= 0.7	1.00

4.1.2. Structure Loading of Observed Indicators

Structure loadings indicate latent variable-observed indicator relationships in SEM analysis, assessing the validity and reliability of measurement models. High loadings (>0.5) confirm the measurement of latent constructs. In organizational research, factor loadings above 0.70 indicate significant connections and convergent validity, ensuring trustworthy measurement and causal model validation (Epebinu, Adepoju, & Ajayi, 2023; Williams, O'Boyle, & Yu, 2020). Financial structures affect important stock banking indicators differently, as shown in Table 2.

SMA has good loadings with ICICI at 0.914 and SBI at 0.897, supporting Agrawal et al. (2022)'s claim that SMA predicts stock prices. RSI reveals significant loadings, with ICICI (0.852) responding the most and SBI (0.807) the least, demonstrating varying sensitivity to market momentum across firms, confirmed by Jeong et al. (2021). VWAP shows large volume-to-price loadings for ICICI (0.865) and low loadings for HDFC (0.731), consistent with Jeong et al. (2021). ICICI's PVT loadings are strong (0.864) and HDFC's are lower (0.754), suggesting distinct trade dynamics or market behaviors affect pivot point predictions, corroborated by Cohen (2021).

ATR and CCI reveal moderate to strong loadings, with Axis Bank's CCI loading (0.679) unusually low, indicating a market characteristic, according to Bagga and Patel (2023). Fikri et al. (2022) support Axis Bank's Bollinger Bands (0.605) and SBI's Stochastic (K) (0.564) variability, suggesting that market sensitivity limits forecasting power. These reduced loadings suggest that SEM models may include secondary predictors driven by external market factors.

4.1.3. Composite Reliability (CR)

Composite reliability (CR) measures item internal consistency, reflecting latent variable representation. CR is better for indicator reliability than Cronbach's Alpha for Structural Equation Modeling (SEM) because it accounts for factor loadings and measures consistency more precisely (Hair Jr, Howard, & Nitzl, 2020). Internal consistency is usually shown by CR scores above 0.70. Table 2 shows outstanding consistency with CR values ranging from 0.802 (Stochastic) to 0.932 (SMA), confirmed by Hair Jr et al. (2020). Recent investigations support SMA's CR of 0.932, demonstrating resilience in measuring the construct (Borrillo & Panteghini, 2023; Nobre et al., 2023; Yongmei & Yiyang, 2021). Lai and Hsiao (2022) stress the importance of correct CR measurement to eliminate bias. Fu, Wen, and Wang (2022) found that CR provides robust reliability estimates for constructing internal consistency validation.

4.1.4 Average Variance Extracted (AVE)

The average variance extracted (AVE) analyzes a construct's indicator variance versus measurement error, with convergent validity at 0.5 or greater. When the square root of the AVE surpasses inter-construct correlations, discriminant validity is proven (Herlambang et al., 2021). Convergent validity is confirmed by high AVE values, indicating that constructs represent latent variables (Alotaibi, 2021; Yang et al., 2022). Table 2 provides AVE values ranging from 0.513 (Stochastic) to 0.774 (SMA). SMA and RSI have good convergent validity with AVEs of 0.774 and 0.687, while Stochastic's AVE is barely above the threshold. Wang et al. (2020) show that technical indicator constructions make consistent, trustworthy predictions in SEM analysis.

Table 2. Structure loading, composite reliability, AVE, and Cronbach's alpha.

Constructs	Items	Loading	Composite reliability (CR)	Average variance extracted (AVE)	Cronbach' s alpha	Full collinearity (VIFs)
SMA	1: SMA of axis	0.838	0.932	0.774	0.902	2.773
	2: SMA of SBI	0.897				
	3: SMA of HDFC	0.869				
	4: SMA of ICICI	0.914				
RSI	1: RSI of axis	0.818	0.898	0.687	0.848	2.236
	2: RSI of SBI	0.807				
	3: RSI of HDFC	0.838				
	4: RSI of ICICI	0.852				
VWAP	1: VWAP of axis.	0.862	0.894	0.678	0.840	2.424
	2: VWAP of SBI	0.829				
	3: VWAP of HDFC.	0.731				
	4: VWAP of ICICI	0.865				
PVT	1: PVT of axis	0.798	0.881	0.650	0.820	3.652
	2: PVT of SBI	0.806				
	3: PVT of HDFC	0.754				
	4: PVT of ICICI	0.864				
ATR	1: ATR of axis	0.752	0.849	0.585	0.763	1.354
	2: ATR of SBI	0.764				
	3: ATR of HDFC	0.732				
	4: ATR of ICICI	0.810				
CCI	1: CCI of axis	0.679	0.834	0.559	0.735	1.918
	2: CCI of SBI	0.726				
	3: CCI of HDFC	0.761				
	4: CCI of ICICI	0.816				
MACD	1: MACD of axis.	0.713	0.830	0.550	0.727	1.610
	2: MACD of SBI	0.780				
	3: MACD of HDFC	0.721				
	4: MACD of ICICI	0.750				
Bollinger	1: BOLL of axis	0.605	0.812	0.522	0.691	1.563
	2: BOLL of SBI	0.769				
	3: BOLL of HDFC	0.711				
	4: BOLL of ICICI	0.791				
Stochastic (K)	1: StocK of axis	0.784	0.802	0.513	0.669	2.282
	2: StocK of SBI	0.564				
	3: StocK of HDFC	0.740				
	4: StocK of ICICI	0.822				

4.1.5. Cronbach's Alpha

For established scales, Cronbach's Alpha values above 0.7 indicate internal consistency of construct items. Kuo and Chou (2021) discuss its usage in evaluating the reliability of organizational research concepts. Cronbach's Alpha is prominent, but Composite Reliability provides a more sophisticated assessment of indicator reliability. SEM reliability ranges from high to mediocre, as shown in Table 2 by Cronbach's Alpha values for financial constructs. Stochastic's lower value matches (Edwards, Joyner, & Schatschneider, 2021), while SMA's alpha of 0.902 indicates great internal consistency. With values of 0.848 and 0.840, RSI and VWAP are reliable. PVT has strong internal consistency at 0.820. Other constructs—ATR (0.763), CCI (0.735), and MACD (0.727)—are suitable.

4.1.6. Full Collinearity

The regression model predictor multicollinearity is assessed using VIF values. Low inter-correlations ensure model integrity with multicollinearity below 3.0 (Herlambang et al., 2021). Table 2 lists all constructs with VIFs below this level except PVT at 3.652, which is acceptable. Model validity is increased by confirming each variable's distinct contribution. Strong evaluations of the SEM model's Composite Reliability, Average Variance Extracted, Cronbach's Alpha, and Full Collinearity VIFs show measurement reliability. SMA and RSI are useful SEM constructs due to their internal consistency and convergent validity. Validation boosts research credibility and rigor.

4.2. Discriminant Validity Test Results

Table 3 shows a matrix comparing variable correlations against the square roots of the Average Variance Extracted (AVE) for each construct to test discriminant validity in SEM analysis. To provide model robustness, the SEM framework has unique structures. The Heterotrait-monotrait (HTMT) ratio, emphasized in E-Government adoption studies (Almufti, Sellami, & Belguith, 2024), and the Fornell-Larcker criterion rigorously evaluate discriminant validity (Herlambang et al., 2021), confirming that constructs correlate more strongly with their own measures than with others, ensuring uniqueness and empirical validity (Howard & Van Zandt, 2020).

The SMA, RSI, VWAP, PVT, ATR, CCI, MACD, Bollinger Bands, and Stochastic Oscillator (K) diagonal values (square root of AVE) exceed inter-construct correlations in empirical validation. The SMA has good discriminant validity because its diagonal value of 0.880 exceeds its correlations with the RSI (0.568) and VWAP (0.662). The diagonal value of the RSI is 0.829, while its highest correlation with PVT is 0.676. The VWAP and PVT diagonals are 0.824 and 0.806, respectively. With diagonal values of 0.765 and 0.747, ATR and CCI have low correlations with other constructs, confirming their discriminant validity (the highest being 0.601 with Stock for ATR and 0.546 with PVT for CCI). The MACD has a diagonal of 0.742 and correlates 0.447 with CCI, while Bollinger Bands correlate 0.495 with VWAP. With a diagonal of 0.717, the Stochastic Oscillator (K) has better discriminant validity than other construct correlations. These validations demonstrate each construct's unique contributions to the model, confirming the SEM framework's integrity and independence and verifying the study's theoretical implications.

Table 3. Discriminant validity test results: correlations among independent variables and square roots of AVEs.

Constructs	1	2	3	4	5	6	7	8	9
1. SMA	0.880								
2. RSI	0.568	0.829							
3. VWAP	0.662	0.533	0.824						
4. PVT	0.690	0.676	0.630	0.806					
5. ATR	0.329	0.298	0.362	0.292	0.765				
6. CCI	0.583	0.511	0.505	0.546	0.382	0.747			
7. MACD	0.420	0.384	0.421	0.399	0.311	0.447	0.742		
8. Bollinger	0.452	0.339	0.495	0.365	0.325	0.325	0.325	0.723	
9. StocK	0.271	0.458	0.567	0.401	0.601	0.346	0.385	0.391	0.717

4.3. Path Coefficients and Significance Levels

The path analysis of Table 4's coefficients and p-values shows that various technical indicators predict the Bank Nifty Index's volume and closing values. Significant links are supported by strong positive correlations, such as PVT on closing value (0.369, $p < 0.001$) and VWAP on volume (0.262, $p < 0.001$). This validates the findings of Caldera and Lavanya (2020) and Stein (2024), who found that many indicators work in volatile markets. Liu and Pan (2020) show that many technical characteristics can improve volatility prediction.

Ayala et al. (2021)'s findings on machine learning's usefulness in trading signals show that ensemble algorithms using historical and technical data (RSI, MACD) anticipate market trends. The evidence rejects assumptions for ATR and Bollinger bands, indicating their conditional limits. . George, Nair, and Yathish (2022) and Mohammed (2022) explore the need for transformation or algorithmic underpinning to improve indicator efficacy, and Liu and Pan (2020) show that a combination of indicators during economic booms provides better projections. Low coefficients for indicators like MACD reflect their limited use in difficult markets, with Pardeshi and Kale (2021) assessing their efficacy under different scenarios. Bouasabah and Khalaf (2023)'s stochastic model and Nabipour et al. (2020) 's deep learning algorithms demonstrate technical indicators' increased predictive power. Jayaraman and Venkatachalam (2021)'s usage of neural networks for NIFTY 50 trend predictions validates the association between volume and closing values (0.142, $p < 0.001$). This highlights the predictive importance of volume data. Ayala et al. (2021) and Dhafer et al. (2022) also show that technical indicators improve stock prediction and trading signals.

Table 4. Path coefficients and p-values of the model.

Hypotheses	Path	Path coefficient	P values	Acceptance/Rejection of hypothesis
Ha 1	SMA → Volume	0.189	< 0.001	Accepted
Hb 2	SMA → Closing value	0.169	< 0.001	Accepted
Ha 3	RSI → Volume	0.149	< 0.001	Accepted
Hb 4	RSI → Closing value	0.076	< 0.050	Accepted
Ha 5	VWAP → Volume	0.262	< 0.001	Accepted
Hb 6	VWAP → Closing value	0.091	< 0.050	Accepted
Ha 7	PVT → Volume	0.132	< 0.001	Accepted
Hb 8	PVT → Closing value	0.369	< 0.001	Accepted
H_1 9	ATR → Volume	0.062	0.081	Rejected
Ha 10	ATR → Closing value	0.132	< 0.050	Accepted
Hb 11	CCI → Volume	0.205	< 0.001	Accepted
Ha 12	CCI → Closing value	0.065	0.070	Rejected
Hb 13	MACD → Volume	0.051	0.123	Rejected
H_1 14	MACD → Closing value	0.122	< 0.050	Accepted
Ha 15	Bollinger → volume	0.040	0.185	Rejected
Hb 16	Bollinger → Closing value	0.030	0.252	Rejected
Ha 17	StocK → Volume	0.004	0.468	Rejected
Hb 18	StocK → Closing value	0.278	< 0.001	Accepted
Ha 19	Volume → Closing value	0142	< 0.001	Accepted

Table 5. Indirect effects of constructs on closing value for paths with two segments.

Path	Path coefficient	P values	Effect size	Outcome whether partial mediation or full mediation
SMA → Closing value	0.024	0.222	Small	Partial mediation
RSI → Closing value	0.021	0.249	Small	Partial mediation
VWAP → Closing value	0.037	0.117	Medium	Partial mediation
PVT → Closing value	0.019	0.276	Small	Partial mediation
ATR → Closing value	0.018	0.278	Small	Partial mediation
CCI → Closing value	0.029	0.176	Medium	Partial mediation
Bolling → Closing value	0.006	0.429	Very small	No mediation (Negligible effect)
StocK → Closing value	-0.001	0.494	Very small	No mediation (Negligible and negative effect)
MACD → Closing value	0.007	0.408	Very small	No mediation (Negligible effect)

Table 5 exhibits the indirect effects of technical indicators on NIFTY Bank Index closing values, with varied degrees of influence. VWAP (0.037, p=0.117) and CCI (0.029, p=0.176) have the strongest indirect effects with medium effect sizes, suggesting partial mediation. Caldera and Lavanya (2020) demonstrated that integrating various indicators could better anticipate stock price fluctuations, supporting VWAP and CCI's modestly good indirect impacts. Ensemble models improve predicted accuracy utilizing indicators like CCI, according to Jayaraman and

Venkatachalam (2021) and Ramakrishnan, Devi, Yuvaraaj, Vishnu, and Thinhesh (2023) echo the smaller but significant impacts of SMA (0.024, p=0.222) and RSI (0.021, p=0.249).

Işık (2020) examined how technical indicators might contribute to deep learning-based forecasting models, despite PVT and ATR's weaker indirect impacts (0.019, p=0.276 and 0.018, p=0.278). The minimal to negative effects of Bollinger Bands, Stochastic Oscillator, and MACD show little utility in this scenario. Ayala et al. (2021) suggest that some technical indicators can improve trading techniques, but others may not affect predictive models depending on market conditions.

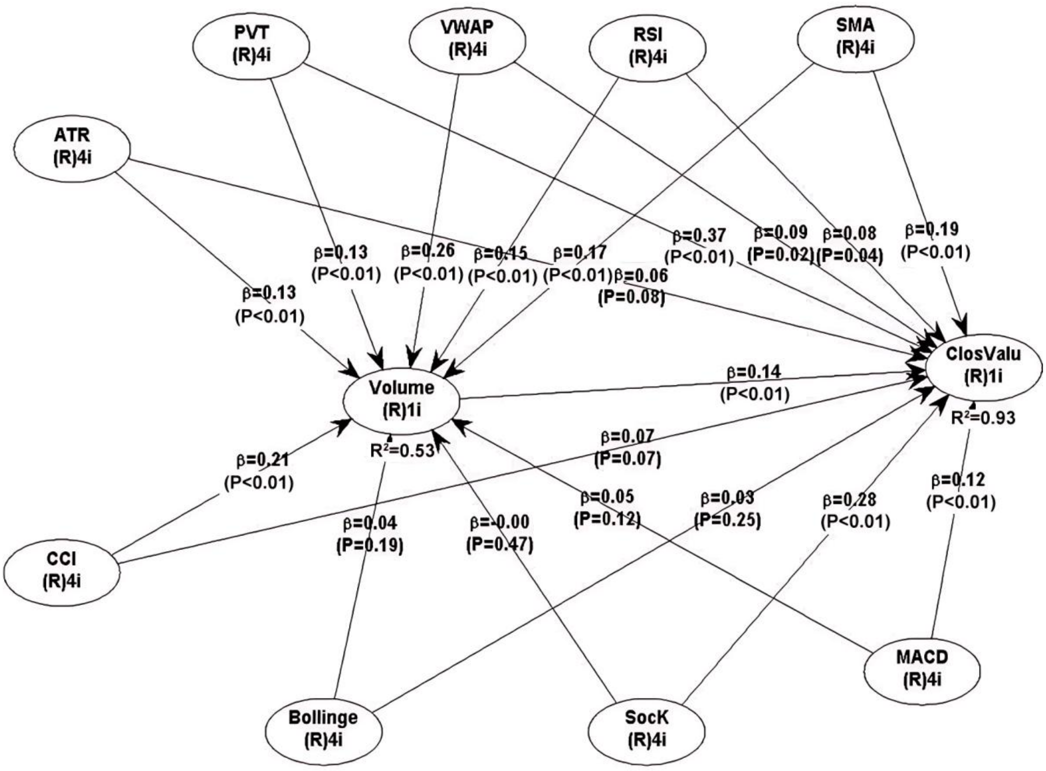

Figure 1. Structural equation model results.

As seen in Figure 1, the outcomes of the SEM illustrate the relationship between selected indicators and their effects on trading volume and closing value. The model suggests that Volume (R[1]i) depends on ATR, PVT, VWAP, RSI, and CCI, with β values ranging from 0.13 to 0.45 (P < .01). Moreover, Closing Value (R[1]i) is influenced by SMA, MACD, Volume, and several other indicators, with an R^2 value of 0.93, indicating a highly informative model. The model helps in understanding the association of these indicators with market movements.

Table 6. T-ratios for path coefficients of the structural equation model.

Constructs	SMA	RSI	VWAP	PVT	ATR	CCI	Bollinger	StocK	MACD
Closing value	4.357	1.733	2.073	8.705	1.399	1.479	0.670	6.490	2.790
Volume	3.882	3.429	6.083	3.012	2.977	4.741	0.897	-0.080	1.161

Note: Critical T ratios, for one-tailed tests: 1.645 and for two-tailed tests: 1.960.

The analysis shows different significant levels using one-tailed (1.645) and two-tailed (1.960) critical T ratios (Table 6). Saputra, Izzatunnisa, Lucky, and Iswanto (2023) show that the SMA and PVT indicators, with T ratios of 4.357 and 8.705, greatly exceed these standards, confirming their strong closing value prediction reliability. T ratios of -0.080 and 0.670 for the Stochastic Oscillator and Bollinger Bands underperform the essential values and reflect questionable prediction power under certain conditions (Hazir & Danisman, 2021). VWAP and CCI had T ratios of 6.083 and 4.741 for trade volume, showing strong predictions. RSI, ATR, and Bollinger Bands have decreased significance, with the Stochastic Oscillator and Bollinger Bands' T ratios again dropping below the thresholds, demonstrating their poor forecasting effectiveness in this model (Jeong et al., 2021). Technical indicators predict closing values and volume distinctly for the Bank Nifty Index. They specifically point out that SMA and PVT are good indicators of closing values while VWAP and CCI are good indicators of volume. The residual significance of RSI, ATR, OLS, and the Precise Stochastic Oscillator and Bollinger Bands indicates the low forecasting usefulness of these variables.

This research illustrates a distinct connection between the power of prediction of technical indicators and their effectiveness on trading volumes and closing prices of the Bank Nifty Index. The Simple Moving Average (SMA) and Price Volume Trend (PVT) were major path coefficient determinants; hence, they can be used in predicting the closing price. These conclusions confirm the premise that there are indeed some indicators that are more powerful in ascertaining some, but not all, market variables. The "Volume Weighted Average Price" (VWAP) and the trading poise relationship prove, even more, the significance of price as well as volume indicators regarding market activity. On the other hand, the lower path coefficients and T ratios of other indicators, such as Bollinger Bands and Stochastic Oscillators, demonstrate how little they may apply in the given market situation. This differentiation illustrates the multifaceted nature of the application of indicators, where some instruments are more effective than others under certain conditions, while others provide little information. Combining these findings, the study not only posits which indicators work best but also elucidates the relationship between technical issues and the resulting market phenomena. This holistic view of the results provides further depth to the practical applicability of the findings, making it easier for traders and scholars to effectively formulate trading scenarios and accurately predict market behavior.

4.4. Summary of Results and Discussions

The outcomes of this analysis reveal both the potential and the relationships of the indicators with respect to the Bank Nifty Index regarding its forecasting and trading analysis. It was found that the Simple Moving Average (SMA), Price Volume Trend (PVT), and Volume Weighted Average Price (VWAP) were good predictors of trading volumes and closing values, supported by reasonably significant path coefficients and T-ratios that confirm their fitness for market capture and use in decision-making. However, some indicators like Bollinger Bands and the Stochastic Oscillator had limited applicability because they produced lower path coefficients. Some others, like the CCI and MACD, portrayed strength, but that strength was circumstantial, emphasizing the need for proper indicator selection in the given market situation. The SEM model employed in this research corroborated these conclusions with very good model fit indices; for instance, the average R-squared was 72.9%, and the Tenahnus GoF was 0.706, which indicates good performance of the model in explaining the market but poor multicollinearity.

These results lead to niche trading insights for different segments of the market because SMA and RSI work exceptionally well in showing directional movements, while VWAP and CCI provide a broader scope by offering deeper insights and implications on trading volumes. The results ultimately demonstrate that, even though each individual indicator may have advantages and disadvantages, their combined application fosters a synergistic interaction that renders them vital in understanding the market, making them essential for achieving effective trading and market research efforts. From a broader perspective, this analysis strengthens the position of technical indicators in estimating market movements and improving trading strategies, as well as proving that SEM is useful in revealing the intricate connections between these indicators, adding value to the theory and practice of financial analysis.

5. CONCLUSION AND IMPLICATIONS OF THE STUDY

5.1. Conclusion

Using Structural Equation Modeling (SEM) to make predictions based on technical indicators of the Nifty Bank Index has unique relevance in understanding financial markets. This study improves upon previous research by successfully developing a SEM model incorporating SMA, RSI, and MACD, thus underscoring the significance of including each of these tools in the analysis of finance. Our analysis reveals that SEM can be used in pattern recognition and quantification of interdependence between several parameters, leading to the development of a model that could explain nearly 72.9% of the variations in trading volumes and closing prices, with an Average R-squared (ARS) of 0.729 ($p<0.001$).

This exploration highlights how important it is for investors to be able to strategize using several technical indicators within the market to improve the forecasts made. Through the presented path coefficients, such as 0.369 ($p<0.001$), the effect of Pivot Points on closing prices suggests a significant positive impact that some selected indicators have on market performance as well. Moreover, a detailed analysis of T Ratios shows that among the studied indicators, the SMA and PVT indicators are best capable of forecasting closing values, while the VWAP and CCI indicators are the most useful in predicting trading volumes. On the other hand, the lesser effectiveness of indicators like the Stochastic Oscillator and the Bollinger Bands, due to their low T Ratios, means that there is a need to focus on the use of quantitative measures in determining the types of technical indicators to be used and the market conditions to which they are to be applied.

Besides the adequate scores of the SEM model in previous parts, other excellent fit indices enhance its structural strength and predictive validity. For example, the Goodness of Fit (GoF) index, Tenenhaus GoF, was 0.706. This shows that not only can the model predictions be accurate, but that the model itself has an overall fit. The vindications of SEM as an operational model for market predictions are reinforced.

5.2. Theoretical Implications

The new advancement in understanding the practical implementation of SEM successfully integrates and evaluates different technical indicators, improving our skills in the usage of these instruments in the financial market. The study proved that complex interrelations between such indicators as SMA, RSI, and MACD can be implemented quantitatively, which allows for a more in-depth understanding of how these indicators act in generating market activity. This not only adds empirical value to the theoretically based literature on market assessment, but it also adds a new dimension to the market's behavioral analysis as postulated by Emmanuel and Ejike (2020). The ideas presented in this study emphasize the necessity of using multiple indicators for analysis, which provides more comprehensive access to the analyzed phenomena in general and more efficient approaches for constructing and testing economic theories. The empirical use of SEM in financial market evaluation does not only bridge the divide between practice and theory but also improves the analytical power of all players in financial markets, which eventually contributes to enhanced strategic financial management and a more resilient financial market system.

In expanding the current research, the marketplace finance analysis is made in this study's contribution to the development of understanding of the market. A more interesting analysis of the market synergies is conducted through the adoption of Structural Equation Modelling (SEM) and popular technical analysis indicators such as SMA, RSI, and MACD. Earlier works by Herwartz and Xu (2022) and Mohanty et al. (2021) focused on investor attention and market volatility employing SEM. Our research goes one step further and demonstrates that SEM can be employed to model several different technical indicators to improve the overall performance of the model to an average R-squared of 72.9%, which is very impressive.

Let us not forget that, although earlier studies focused on the effectiveness of technical indicators, for example, how they feature SMA for trend analysis (Ayala et al., 2021) or how Zhu et al. (2019) mentioned it for volatility forecasting, this study demonstrates that these indicators work in multivariate contexts together to improve predictive accuracy. The results noted that closing prices are best forecasted when both SMA and PVT are used, which is consistent with Mohanty et al. (2021), who confirmed the effectiveness of SMA. Similarly, Jeong et al. (2021) show that volume indicators, such as VWAP and CCI, are also useful in forecasting trading volumes.

This study, like previous studies by Zhang and Cai (2021), fills the gap between SEM theory and practical application. It also builds upon existing methods by using additional fit indices, such as the Tenenhaus GoF, and testing the strength of the model's structure, in this case, the SEM analysis of the Nifty Bank Index. Such a holistic approach enables us to explain how markets behave and prescribes how practitioners should act, thereby highlighting the importance of SEM in research and practice.

Such connections to past works reinforce and justify the contributions of the paper while acknowledging its role in furthering the field of financial analysis, for example, in blending technical indicators with modeling and forecasting.

5.3. Practical Implications

This study demonstrates the practicality of employing Structural Equation Modeling (SEM) in stock investments in the banking sector, pointing out that it is effective in improving predictive analytics among investors, financial analysts, and institutional investors. The empirical strength of the SEM approach makes it an essential tool for improving strategic decision-making. This methodological complexity allows for the proper differentiation of weights for technical parameters that impact the intensity of trade and price fluctuations, thus making portfolio management more efficient and profitable.

The use of SEM in conjunction with other technical indicators is not only useful in shaping advanced trading techniques but also enhances the accuracy of market projections. Modifying these approaches to the present market as well as its predicted features helps investors make their investment strategies efficient, translating into improved risk management and possibly better returns. This possibility of changing the technical indicators according to the internal requirements of the prevailing market conditions is a significant advantage as far as the strategic positioning of the investors is concerned since global financial markets are known to be very volatile. In addition, the results of this study further support the need for a more integrative view of the market. Through the application of several indicators at the same time, financial managers and analysts would be able to devise more constructive investment and risk management strategies. SEM offers the most lucid description of the interrelations and the impact of various indicators on the market, which also aids in the decision-making process and is of great essence to the financial and strategic management of portfolios.

In a practical sense, practitioners of SEM approach the problem of utilizing econometric models that have been developed theoretically and in such a way that they can be used in the practice of trading in financial markets, thus overcoming the disconnection between academic and professional work. This development enhances decision-making for the better and creates a more profound understanding and analysis of the market's trends and flows. Because it allows investors to accurately determine the entrance and exit points during stock trading, SEM enhances return maximization while minimizing exposure to risks, which in turn advocates for better investment decisions and higher returns. In conclusion, this research encourages the application of econometric analysis to stock market practice to improve the levels of strategic investment management and effectiveness in a fast-changing market.

The result of this research provides several useful suggestions for the stabilization and enhancement of the functioning of financial markets. First, the ability of some technical indicators, such as SMA, RSI, and VWAP, raises the value of using complex methods in the preparation of the market surveillance strategy. It would also be useful if policymakers stimulated business enterprises to use some advanced techniques in trend analysis, such as Structural Equation Modeling (SEM), for more effective market control and risk minimization. Second, the same results suggest the need to concentrate on properly situating strategies to specific environments. Policymakers may use these findings to aid in improving their regulations regarding the limits of trading activity and the liquidity of the market, making the policies more responsive to the prevailing market situation.

There is also a need for authoritative suggestions on the appropriate use of these indicators while trading algorithms are being developed based on the finding that the applicability of Bollinger Bands and Stochastic Oscillators has some limitations. This could include establishing some baseline standards for testing how useful the indicators are under the changing environments of the financial markets. In addition, this study increases confidence in the use of SEM as a means of collecting information for issuing warning signals for the potential breakdown of the market. In this regard, it is possible for policymakers to start using SEM strain analysis as part of their monitoring system to catch unusual trading activities and minimize their negative effects on the market.

Finally, considering the nature of the international financial system, it is worth stressing the need for these policymakers to put in place financial education campaigns that empower investors with the information related to the use of technical indicators. Such a move would enable retail and institutional investors to exercise their right to choose confidently, thereby fostering a more robust and broad-based financial market system.

6. LIMITATIONS DIRECTIONS FOR FUTURE RESEARCH

This research offers broad expertise on how to make use of SEM and technical indicators in the context of the Nifty Bank Index. However, concentration on the specific banking stocks could be a restraining factor when it comes to making extrapolations in other domains or other geographical markets. Further studies could use the same analytical framework but in different segments of the market or in a different economic climate to assess its robustness and adaptability. Moreover, efforts combining state-of-the-art machine learning techniques and different types of data sets could enhance predictive capabilities and the detail of the analyses, providing new opportunities for complex financial models and market prediction approaches. Such continuous efforts in seeking and utilizing different analytical angles will also enhance the scope of financial market analysis and aspects of such studies that are both theoretical and practical in nature.

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REFERENCES

Agrawal, M., Shukla, P. K., Nair, R., Nayyar, A., & Masud, M. (2022). Stock prediction based on technical indicators using deep learning model. *Computers, Materials & Continua, 70*(1), 287–304. https://doi.org/10.32604/cmc.2022.014637

Agudelo Aguirre, A. A., Duque Méndez, N. D., & Rojas Medina, R. A. (2021). Artificial intelligence applied to investment in variable income through the MACD (moving average convergence/divergence) indicator. *Journal of Economics, Finance and Administrative Science, 26*(52), 268-281.

Alexakis, C., Pappas, V., & Skarmeas, E. (2021). Market abuse under different close price determination mechanisms: A European case. *International Review of Financial Analysis, 74*, 101707. https://doi.org/10.1016/j.irfa.2021.101707

Alexopoulos, C., Boone, J. H., Goldsman, D., Lolos, A., Dingeç, K. D., & Wilson, J. R. (2020). *Steady-state quantile estimation using standardized time series.* Paper presented at the Winter Simulation Conference (WSC), 289–300.

Alfonso, G., Carnerero, A. D., Ramirez, D. R., & Alamo, T. (2021). Receding horizon optimization of large trade orders. *IEEE Access, 9*, 63865-63875. https://doi.org/10.1109/ACCESS.2021.3075700

Alfonso, G., & Ramirez, D. R. (2020). A nonlinear technical indicator selection approach for stock markets. Application to the Chinese stock market. *Mathematics, 8*(8), 1301. https://doi.org/10.3390/math8081301

Alkhatib, K., Khazaleh, H., Alkhazaleh, H. A., Alsoud, A. R., & Abualigah, L. (2022). A new stock price forecasting method using active deep learning approach. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(2), 96. https://doi.org/10.3390/joitmc8020096

Almufti, M., Sellami, R., & Belguith, L. H. (2024). *Validation of a measuring model as a key aspect in the adoption of e-government in developing countries*. Paper presented at the 2024 5th International Conference on Advancements in Computational Sciences (ICACS), 1–7.

Alotaibi, S. S. (2021). Ensemble technique with optimal feature selection for Saudi stock market prediction: A novel hybrid red deer-grey algorithm. *IEEE Access, 9*, 64929-64944.

Alsubaie, Y., El Hindi, K., & Alsalman, H. (2019). Cost-sensitive prediction of stock price direction: Selection of technical indicators. *IEEE Access, 7*, 146876-146892. https://doi.org/10.1109/ACCESS.2019.2945907

Ananthi, M., & Vijayakumar, K. (2021). Retracted article: Stock market analysis using candlestick regression and market trend prediction (CKRM). *Journal of Ambient Intelligence and Humanized Computing, 12*(5), 4819-4826. https://doi.org/10.1007/s12652-020-01892-5

Ayala, J., García-Torres, M., Noguera, J. L. V., Gómez-Vela, F., & Divina, F. (2021). Technical analysis strategy optimization using a machine learning approach in stock market indices. *Knowledge-Based Systems, 225*, 107119. https://doi.org/10.1016/j.knosys.2021.107119

Bagga, A. R., & Patel, H. (2023). Stock market forecasting using ensemble learning and statistical indicators. *Journal of Engineering Research, 11*(3), 1–15.

Ballová, D. (2020). Trend analysis and detection of change-points of selected financial and market indices. *Information Technology, Systems Research, and Computational Physics, 3*, 372–381.

Bhatia, P., & Gupta, P. (2020). Sub-prime crisis or COVID-19: A comparative analysis of volatility in Indian banking sectoral indices. *FIIB Business Review, 9*(4), 286-299. https://doi.org/10.1177/2319714520972210

Bildirici, M., Şahin Onat, I., & Ersin, Ö. Ö. (2023). Forecasting BDI sea freight shipment cost, VIX investor sentiment and MSCI global stock market indicator indices: Lstar-garch and lstar-apgarch models. *Mathematics, 11*(5), 1242.

Borrillo, F., & Panteghini, M. (2023). Current performance of C-reactive protein determination and derivation of quality specifications for its measurement uncertainty. *Clinical Chemistry and Laboratory Medicine, 61*(9), 1552-1557.

Bouasabah, M., & Khalaf, O. I. (2023). A technical indicator for a short-term trading decision in the NASDAQ market. *Advances in Decision Sciences, 27*(3), 1-13.

Branch, B. S., Ma, A. J., & Orland, W. (2018). Using pivot table to test market anomaly. *Available at SSRN 2992371*. https://doi.org/10.2139/ssrn.2992371

Brandt, H., Umbach, N., Kelava, A., & Bollen, K. A. (2020). Comparing estimators for latent interaction models under structural and distributional misspecifications. *Psychological Methods, 25*(3), 321–345. https://doi.org/10.1037/met0000231

Bustos, O., & Pomares-Quimbaya, A. (2020). Stock market movement forecast: A systematic review. *Expert Systems with Applications, 156*, 113464. https://doi.org/10.1016/j.eswa.2020.113464

Caldera, H. A., & Lavanya, W. P. A. (2020). *Combinatorial impact of technical indicators on price prediction in colombo stock market*. Paper presented at the 2020 20th International Conference on Advances in ICT for Emerging Regions (ICTer), 256–261.

Chang, T.-H., Wang, N., & Chuang, W.-B. (2021). Stock price prediction based on data mining combination model. *Journal of Global Information Management, 30*(7), 1-19.

Chen, C.-H., Lai, W.-H., Hung, S.-T., & Hong, T.-P. (2022). An advanced optimization approach for long-short pairs trading strategy based on correlation coefficients and bollinger bands. *Applied Sciences, 12*(3), 1052. https://doi.org/10.3390/app12031052

Chen, Y., Fang, R., Liang, T., Sha, Z., Li, S., Yi, Y., . . . Song, H. (2021). Stock price forecast based on CNN-BiLSTM-ECA model. *Scientific Programming, 2021*(1), 2446543.

Chin, W., Cheah, J.-H., Liu, Y., Ting, H., Lim, X.-J., & Cham, T. H. (2020). Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. *Industrial Management & Data Systems, 120*(12), 2161-2209. https://doi.org/10.1108/IMDS-10-2019-0529

Cho, G., & Hwang, H. (2023). Structured factor analysis: A data matrix-based alternative approach to structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *30*(3), 364-377. https://doi.org/10.1080/10705511.2022.2126360

Cho, G., Kim, S., Lee, J., Hwang, H., Sarstedt, M., & Ringle, C. M. (2023). A comparative study of the predictive power of component-based approaches to structural equation modeling. *European Journal of Marketing*, *57*(6), 1641-1661. https://doi.org/10.1108/EJM-07-2020-0542

Choi, S.-Y. (2021). Analysis of stock market efficiency during crisis periods in the US stock market: Differences between the global financial crisis and COVID-19 pandemic. *Physica A: Statistical Mechanics and Its Applications*, *574*, 125988. https://doi.org/10.1016/j.physa.2021.125988

Coe, T. S., & Laosethakul, K. (2021). Applying technical trading rules to beat long-term investing: Evidence from Asian markets. *Asia-Pacific Financial Markets*, *28*(4), 587-611. https://doi.org/10.1007/s10690-021-09337-5

Cohen, G. (2021). Optimizing algorithmic strategies for trading bitcoin. *Computational Economics*, *57*(2), 639-654. https://doi.org/10.1007/s10614-020-09972-6

Cohen, G. (2022). Algorithmic strategies for precious metals price forecasting. *Mathematics*, *10*(7), 1134. https://doi.org/10.3390/math10071134

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092. https://doi.org/10.1016/j.techfore.2021.121092

Delis, P., Degiannakis, S., & Giannopoulos, K. (2023). What should be taken into consideration when forecasting oil implied volatility index? *The Energy Journal*, *44*(5), 231-250.

Dhafer, A. H., Mat Nor, F., Alkawsi, G., Al-Othmani, A. Z., Ridzwan Shah, N., Alshanbari, H. M., . . . Baashar, Y. (2022). Empirical analysis for stock price prediction using NARX model with exogenous technical indicators. *Computational Intelligence and Neuroscience*, *2022*(1), 9208640. https://doi.org/10.1155/2022/9208640

Duffie, D., & Dworczak, P. (2021). Robust benchmark design. *Journal of Financial Economics*, *142*(2), 775-802. https://doi.org/10.1016/j.jfineco.2021.01.004

Edwards, A. A., Joyner, K. J., & Schatschneider, C. (2021). A simulation study on the performance of different reliability estimation methods. *Educational and Psychological Measurement*, *81*(6), 1089-1117. https://doi.org/10.1177/0013164421994184

Emmanuel, O., & Ejike, D. E. (2020). Globalization and economic environment: Nigerian experience from 1990-2018. *Globalization*, *2*(1&2), 119-137.

Epebinu, O., Adepoju, A., & Ajayi, M. (2023). E-compensation management and organisational performance: An empirical evaluation using partial least squares-structural equation modelling. *International Journal of Management Studies and Social Science Research*, *142*. https://doi.org/10.56293/ijmsssr.2022.4623

Falke, A., Schröder, N., & Endres, H. (2020). A first fit index on estimation accuracy in structural equation models. *Journal of Business Economics*, *90*, 277-302. https://doi.org/10.1007/s11573-019-00952-3

Figini, S., Maggi, M., & Uberti, P. (2020). The market rank indicator to detect financial distress. *Econometrics and Statistics*, *14*, 63-73.

Fikri, N., Moussaid, K., Rida, M., El Omri, A., & Abghour, N. (2022). A channeled multilayer perceptron as multi-modal approach for two time-frames algo-trading strategy. *International Journal of Advanced Computer Science and Applications*, *13*(2).

Frei, C., & Mitra, J. (2021). Optimal closing benchmarks. *Finance Research Letters*, *40*, 101674. https://doi.org/10.1016/j.frl.2020.101674

Fu, Y., Wen, Z., & Wang, Y. (2022). A comparison of reliability estimation based on confirmatory factor analysis and exploratory structural equation models. *Educational and Psychological Measurement*, *82*(2), 205-224. https://doi.org/10.1177/00131644211008953

Garnier-Villarreal, M., & Jorgensen, T. D. (2020). Adapting fit indices for Bayesian structural equation modeling: Comparison to maximum likelihood. *Psychological Methods*, *25*(1), 46-70. https://doi.org/10.1037/met0000224

George, J., Nair, A. M., & Yathish, S. (2022). *Analysis of market behavior using popular digital design technical indicators and neural network*. Paper presented at the In Expert Clouds and Applications: Proceedings of ICOECA 2021 (pp. 445-458). Springer Singapore.

Gil-Alana, L. A., Abakah, E. J. A., & Rojo, M. F. R. (2020). Cryptocurrencies and stock market indices. Are they related? *Research in International Business and Finance, 51*, 101063. https://doi.org/10.1016/j.ribaf.2019.101063

Gong, X., & Lin, B. (2021). Effects of structural changes on the prediction of downside volatility in futures markets. *Journal of Futures Markets, 41*(7), 1124-1153. https://doi.org/10.1002/fut.22207

Hair Jr, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101-110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hazir, U., & Danisman, T. (2021). *Deep q-learning for stock future value prediction trends in data engineering methods for intelligent systems*. Paper presented at the Proceedings of the International Conference on Artificial Intelligence and Applied Mathematics in Engineering (ICAIAME 2020), 350–359.

He, H., Li, S., Wang, S., Li, B., Zhao, J., & Ma, F. (2022). Investment strategies under stochastic electricity prices and implications for charging infrastructure network coverage: A case of photovoltaic pavements. *Computers & Industrial Engineering, 172*, 108523. https://doi.org/10.1016/j.cie.2022.108523

Herlambang, H., Fitri, A. D., Mukminin, A., Muhaimin, M., Hidayat, M., Elfiani, E., . . . Salam, A. A. (2021). Quality assurance for sustainable higher education: Structural equation modeling. *Sustainability, 13*(9), 4954. https://doi.org/10.3390/su13094954

Herwartz, H., & Xu, F. (2022). Structural transmissions among investor attention, stock market volatility and trading volumes. *European Financial Management, 28*(1), 260-279. https://doi.org/10.1111/eufm.12315

Howard, M. C., & Van Zandt, E. C. (2020). The discriminant validity of honesty-humility: A meta-analysis of the HEXACO, big five, and dark triad. *Journal of Research in Personality, 87*, 103982. https://doi.org/10.1016/j.jrp.2020.103982

Işık, Z. (2020). *The analysis and forecasting of stock price with deep learning*. Paper presented at the 2020 28th Signal Processing and Communications Applications Conference (SIU), 1–4.

Jayaraman, G., & Venkatachalam, M. (2021). *Predicting daily closing value of Indian stock index through artificial neural network*. Paper presented at the 2021 International Conference on Decision Aid Sciences and Application (DASA), 828–837.

Jeong, S. H., Lee, H. S., Nam, H., & Oh, K. J. (2021). Using a genetic algorithm to build a volume weighted average price model in a stock market. *Sustainability, 13*(3), 1011. https://doi.org/10.3390/su13031011

Jiang, M., Jia, L., Chen, Z., & Chen, W. (2022). The two-stage machine learning ensemble models for stock price prediction by combining mode decomposition, extreme learning machine and improved harmony search algorithm. *Annals of Operations Research, 309*(2), 553–585. https://doi.org/10.1007/s10479-020-03690-w

Jobst, L. J., Bader, M., & Moshagen, M. (2023). A tutorial on assessing statistical power and determining sample size for structural equation models. *Psychological Methods, 28*(1), 207. https://doi.org/10.1037/met0000423

Karaca, Y., Zhang, Y.-D., & Muhammad, K. (2020). Characterizing complexity and self-similarity based on fractal and entropy analyses for stock market forecast modelling. *Expert Systems with Applications, 144*, 113098. https://doi.org/10.1016/j.eswa.2019.113098

Kasparinsky, F. O. (2022). Complex indicators of the multitrading system. *Scientific Services & Internet, 24*, 248–311.

Ke, H., Zuominyang, Z., Qiumei, L., & Yin, L. (2023). Predicting Chinese commodity futures price: An eemd-hurst-lstm hybrid approach. *IEEE Access, 11*, 14841-14858. https://doi.org/10.1109/access.2023.3239924

Khandelwal, S., Gupta, P., Jain, A., Nehra, A., Yadav, G. S., Kushwaha, R., & Ramani, S. (2023). RETRACTED: Machine learning-based probabilistic profitable model in algorithmic trading. *Journal of Electronic Imaging, 32*(1), 013039-013039. https://doi.org/10.1117/1.jei.32.1.013039

Kouaissah, N., Orlandini, D., Ortobelli, S., & Tichý, T. (2020). Theoretical and practical motivations for the use of the moving average rule in the stock market. *IMA Journal of Management Mathematics, 31*(1), 117-138. https://doi.org/https://doi.org/10.1093/imaman/dpz006

Kulshreshtha, S. (2020). An arima-lstm hybrid model for stock market prediction using live data. *Journal of Engineering Science & Technology Review, 13*(4), 1-7. https://doi.org/10.25103/jestr.134.11

Kulshrestha, N., & Srivastava, V. K. (2020). *Synthesizing technical analysis, fundamental analysis & artificial intelligence–an applied approach to portfolio optimisation & performance analysis of stock prices in India.* Paper presented at the 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), 1185–1188.

Kumbhare, P., Kolhe, L., Dani, S., Fandade, P., & Theng, D. (2023). *Algorithmic trading strategy using technical indicators.* Paper presented at the 2023 11th International Conference on Emerging Trends in Engineering & Technology-Signal and Information Processing (ICETET-SIP), 1–6.

Kuo, S.-Y., & Chou, Y.-H. (2021). Building intelligent moving average-based stock trading system using metaheuristic algorithms. *IEEE Access, 9*, 140383-140396. https://doi.org/10.1109/access.2021.3119041

Lai, M. H., & Hsiao, Y.-Y. (2022). Two-stage path analysis with definition variables: An alternative framework to account for measurement error. *Psychological Methods, 27*(4), 568. https://doi.org/10.1037/met0000410

Lee, S., & Kim, C. K. (2022). Monitoring parameter change for time series models with application to location-scale heteroscedastic models. *Journal of Statistical Computation and Simulation, 92*(18), 3885-3916. https://doi.org/10.1080/00949655.2022.2086983

Lee, T. K., Cho, J. H., Kwon, D. S., & Sohn, S. Y. (2019). Global stock market investment strategies based on financial network indicators using machine learning techniques. *Expert Systems with Applications, 117*, 228-242. https://doi.org/10.1016/j.eswa.2018.09.005

Li, X., Wu, P., & Wang, W. (2020). Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong. *Information Processing & Management, 57*(5), 102212. https://doi.org/10.1016/j.ipm.2020.102212

Liang, C., Ma, F., Li, Z., & Li, Y. (2020). Which types of commodity price information are more useful for predicting US stock market volatility? *Economic Modelling, 93*, 642-650. https://doi.org/10.1016/j.econmod.2020.03.022

Liu, L., & Pan, Z. (2020). Forecasting stock market volatility: The role of technical variables. *Economic Modelling, 84*, 55-65. https://doi.org/10.1016/j.econmod.2019.03.007

Luo, J., Demirer, R., Gupta, R., & Ji, Q. (2022). Forecasting oil and gold volatilities with sentiment indicators under structural breaks. *Energy Economics, 105*, 105751. https://doi.org/10.1016/j.eneco.2021.105751

Luo, Q., Shi, Y., Zhou, X., & Li, H. (2021). Research on the effects of institutional liquidation strategies on the market based on multi-agent model. *Computational Economics, 58*(4), 1025-1049. https://doi.org/10.1007/s10614-020-09987-z

Manjunath, C., Marimuthu, B., & Ghosh, B. (2023). Analysis of Nifty 50 index stock market trends using hybrid machine learning model in quantum finance. *International Journal of Electrical and Computer Engineering, 13*, 3549-3560. https://doi.org/10.11591/ijece.v13i3.pp3549-3560

Meng, X., & Taylor, J. W. (2020). Estimating value-at-risk and expected shortfall using the intraday low and range data. *European Journal of Operational Research, 280*(1), 191-202. https://doi.org/10.1016/j.ejor.2019.07.011

Mitchell, D., Białkowski, J., & Tompaidis, S. (2020). Volume-weighted average price tracking: A theoretical and empirical study. *IISE Transactions, 52*(8), 864-889. https://doi.org/10.1080/24725854.2019.1688896

Mittal, S., & Nagpal, C. K. (2022). A predictive analytics framework for opportunity sensing in stock market: 10.48129/kjs. splml. 18993. *Kuwait Journal of Science*. https://doi.org/10.48129/kjs.splml.18993

Moeini Najafabadi, Z., Bijari, M., & Khashei, M. (2020). Making investment decisions in stock markets using a forecasting-Markowitz based decision-making approaches. *Journal of Modelling in Management, 15*(2), 647-659. https://doi.org/10.1108/jm2-12-2018-0217

Mohammed, S. (2022). *The validity of using technical indicators when forecasting stock prices using deep learning models: Empirical evidence using Saudi stocks.* Paper presented at the 2022 14th International Conference on Computational Intelligence and Communication Networks (CICN), 520–524.

Mohanty, D., Parida, A. K., & Khuntia, S. S. (2021). Financial market prediction under deep learning framework using auto encoder and kernel extreme learning machine. *Applied Soft Computing, 99*, 106898. https://doi.org/10.1016/j.asoc.2020.106898

Muruganandan, S. (2020). Testing the profitability of technical trading rules across market cycles: Evidence from India. *Colombo Business Journal*. https://doi.org/10.4038/cbj.v11i1.56

Nabipour, M., Nayyeri, P., Jabani, H., Shahab, S., & Mosavi, A. (2020). Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data; A comparative analysis. *LEEE Access, 8*, 150199-150212. https://doi.org/10.1109/access.2020.3015966

Naik, N., & Mohan, B. R. (2021). Novel stock crisis prediction technique—a study on Indian stock market. *IEEE Access, 9*, 86230-86242.

Nobre, G. C., Gonçalves Duarte, M., da Silva Ramalho, M. H., Flores Sartori, R., Schmitt Marinho, N. F., André Aires Soares, Í., & Valentini, N. C. (2023). Transcultural adaptation, content, and internal structure validity evidence of the perceived efficacy and goal setting system–2 edition for Brazilian children. *Frontiers in Psychology, 14*, 1052897. https://doi.org/10.3389/fpsyg.2023.1052897

Nor, S. M., & Zawawi, N. H. M. (2019). Does technical analysis work in the Russian market? Insights from MICEX (MOEX Russia) Index component stocks. *Economic Annals-XXI/Ekonomičnij Časopis-XXI*, 178.

Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review, 53*(4), 3007-3057. https://doi.org/10.1007/s10462-019-09754-z

Padhi, D. K., & Padhy, N. (2021). Prognosticate of the financial market utilizing ensemble-based conglomerate model with technical indicators. *Evolutionary Intelligence, 14*(2), 1035-1051. https://doi.org/10.1007/s12065-020-00528-z

Pardeshi, Y. K., & Kale, P. (2021). *Technical analysis indicators in stock market using machine learning: A comparative analysis*. Paper presented at the 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 1–6.

Patel, M., Valderrama, C., & Yadav, A. (2022). Metaheuristic enabled deep convolutional neural network for traffic flow prediction: Impact of improved lion algorithm. *Journal of Intelligent Transportation Systems, 26*(6), 730-745. https://doi.org/10.1080/15472450.2021.1974857

Rademaker, M. E. (2020). *Composite-based structural equation modeling*. Wurzburg: Universität Würzburg.

Ramakrishnan, S., Devi, K. R., Yuvaraaj, E., Vishnu, T., & Thinhesh, A. C. (2023). *Ensemble algorithm to speculate stock trend by analyzing technical indicators on historical data*. Paper presented at the 2023 International Conference on Inventive Computation Technologies (ICICT), 970–975.

Ribeiro, G. T., Santos, A. A. P., Mariani, V. C., & dos Santos Coelho, L. (2021). Novel hybrid model based on echo state neural network applied to the prediction of stock price return volatility. *Expert Systems with Applications, 184*, 115490. https://doi.org/10.1016/j.eswa.2021.115490

Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. *Industrial Management & Data Systems, 121*(12), 2637-2650. https://doi.org/10.1108/imds-02-2021-0082

Saputra, B. J., Izzatunnisa, S. Y., Lucky, H., & Iswanto, I. A. (2023). *Stock market prediction system using LSTM with technical indicators as voters*. Paper presented at the 2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS), 229–234.

Savalei, V. (2021). Improving fit indices in structural equation modeling with categorical data. *Multivariate Behavioral Research, 56*(3), 390-407. https://doi.org/10.1080/00273171.2020.1717922

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling*. Mahwah: Psychology Press.

Sehgal, M., & Gupta, S. (2021). Stock Markets in changing times: A study of select global market indices and Indian banks. *International Journal of Business Analytics, 8*(3), 14-25. https://doi.org/10.4018/ijban.2021070102

Shang, Y., & Zheng, T. (2021). Mixed-frequency SV model for stock volatility and macroeconomics. *Economic Modelling, 95*, 462-472. https://doi.org/10.1016/j.econmod.2020.03.013

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis, 70*, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2022). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing, 57*(6), 1662-1677. https://doi.org/10.1108/ejm-08-2020-0636

Singh, J., & Khushi, M. (2021). Feature learning for stock price prediction shows a significant role of analyst rating. *Applied System Innovation, 4*(1), 17. https://doi.org/10.3390/asi4010017

Srivastava, P. R., Zhang, Z. J., & Eachempati, P. (2021). Deep neural network and time series approach for finance systems: Predicting the movement of the Indian stock market. *Journal of Organizational and End User Computing, 33*(5), 204-226. https://doi.org/10.4018/joeuc.20210901.oa10

Stein, T. (2024). Forecasting the equity premium with frequency-decomposed technical indicators. *International Journal of Forecasting, 40*(1), 6-28. https://doi.org/10.1016/j.ijforecast.2022.12.001

Subathra, R. (2021). Classification of Nifty stocks based on pivot points using the principle of nearest neighbourhood. *International Journal on Recent Trends in Business and Tourism, 5*(2), 18-24. https://doi.org/10.31674/ijrtbt.2021.v05i02.004

Vancsura, L., Tatay, T., & Bareith, T. (2023). Evaluating the effectiveness of modern forecasting models in predicting commodity futures prices in volatile economic times. *Risks, 11*(2), 27. https://doi.org/10.3390/risks11020027

Vergura, S. (2020). Bollinger bands based on exponential moving average for statistical monitoring of multi-array photovoltaic systems. *Energies, 13*(15), 3992. https://doi.org/10.3390/en13153992

Wang, P., Ho, T., & Li, Y. (2020). The price-volume relationship of the shanghai stock index: Structural change and the threshold effect of volatility. *Sustainability, 12*(8), 3322. https://doi.org/10.3390/su12083322

Wang, Y., Liu, L., & Wu, C. (2020). Forecasting commodity prices out-of-sample: Can technical indicators help? *International Journal of Forecasting, 36*(2), 666-683. https://doi.org/10.1016/j.ijforecast.2019.08.004

Williams, L. J., O'Boyle, E. H., & Yu, J. (2020). Condition 9 and 10 tests of model confirmation: A review of James, Mulaik, and Brett (1982) and contemporary alternatives. *Organizational Research Methods, 23*(1), 6-29. https://doi.org/10.1177/1094428117736137

Xuan, C., & Kim, C.-J. (2020). Structural breaks in the mean of dividend-price ratios: Implications of learning on stock return predictability. *Japan and the World Economy, 55*, 101027. https://doi.org/10.1016/j.japwor.2020.101027

Xue, Q., Ling, Y., & Tian, B. (2022). Portfolio optimization model for gold and bitcoin based on weighted unidirectional dual-layer LSTM model and SMA-slope strategy. *Computational Intelligence and Neuroscience, 2022*(1), 1869897. https://doi.org/10.1155/2022/1869897

Yang, J., Wang, Y., & Li, X. (2022). Prediction of stock price direction using the LASSO-LSTM model combines technical indicators and financial sentiment analysis. *PeerJ Computer Science, 8*, e1148. https://doi.org/10.7717/peerj-cs.1148

Yıldırım, D. C., Toroslu, I. H., & Fiore, U. (2021). Forecasting directional movement of Forex data using LSTM with technical and macroeconomic indicators. *Financial Innovation, 7*, 1-36. https://doi.org/10.1186/s40854-020-00220-2

Yongmei, H., & Yiyang, W. (2021). Psychometric performance of resilience scale for Chinese adolescent (RSCA) for undergraduates in Guangdong, China. *American Journal of Education and Learning, 6*(2), 86-93. https://doi.org/10.20448/804.6.2.86.93

Zatwarnicki, M., Zatwarnicki, K., & Stolarski, P. (2023). Effectiveness of the relative strength index signals in timing the cryptocurrency market. *Sensors, 23*(3), 1664. https://doi.org/10.3390/s23031664

Zhang, D., & Cai, E. (2021). Improving stock price forecasting using a large volume of news headline text. *Computers, Materials & Continua, 69*(3). https://doi.org/10.32604/cmc.2021.012302

Zhang, J. (2021). Dynamic index optimal investment strategy based on stochastic differential equations in financial market options. *Wireless Communications and Mobile Computing, 2021*(1), 1–9. https://doi.org/10.1155/2021/5545956

Zhang, T. (2021). High-quantile regression for tail-dependent time series. *Biometrika*, *108*(1), 113-126. https://doi.org/10.1093/biomet/asaa046

Zhang, Y., Chu, G., & Shen, D. (2021). The role of investor attention in predicting stock prices: The long short-term memory networks perspective. *Finance Research Letters*, *38*, 101484. https://doi.org/10.1016/j.frl.2020.101484

Zhou, F., Zhou, H.-M., Yang, Z., & Yang, L. (2019). EMD2FNN: A strategy combining empirical mode decomposition and factorization machine based neural network for stock market trend prediction. *Expert Systems with Applications*, *115*, 136-151. https://doi.org/10.1016/j.eswa.2018.07.065

Zhu, Z., Duan, X., & Jun, T. (2019). Relative strength over investment horizons and stock returns. *Journal of Portfolio Management*, *46*(1), 91. https://doi.org/10.3905/jpm.2019.1.111