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Stock Market Analysis: Algorithmic Trading Web Application

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Abstract. Purpose: Algorithmic trading offers a more structured approach to active trading compared to techniques that rely on a trader's intuition or instincts. This study aims to assess the extent of awareness among brokers when they incorporate technology into their trading practices.

Design/Methodology: A series of 350 self-administered questions with a structured format was created and sent to stock brokers who work on the NSE and BSE in the Bangalore district. The Systematic Sampling approach yielded a sample size of 235. To verify the theory, important factors like awareness, automated trading, removing human error, portfolio management, order tracking, and order placement were examined. With the aid of Statistical study Software, the study was carried out utilising Chi-Square and Simple Percentage Analysis (SAS).

Findings: The degree of understanding of the aforementioned technology in its application by the stock brokers of the NSE and BSE operating in Bangalore was shown to have a strong correlation. Among stock brokerage services, automated trading and portfolio management are two closely related uses of algorithmic trading.

Originality: Algorithmic trading uses intricate formulae, mathematical models, and human intervention to determine whether to purchase or sell financial securities on an exchange. It can be applied to many different scenarios, such as trend trading methods, arbitrage, and order execution. High-frequency trading technology, which allows a company to execute tens of thousands of deals per second, is frequently utilised by algorithmic traders.

1. Introduction

Using a computer programme that follows a preset set of rules (an algorithm), an algorithm is used to place a trade in algorithmic trading, often referred to as automated trading [1], black- box trading, or algo-trading. In theory, the transaction can yield gains faster and more frequently than a human trader could [2].

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The given sets of instructions may be predicated on time, money, quantity, or any other variable, as well as on mathematical models. Algo trading improves market liquidity and streamlines trading by reducing the impact of human emotions, in addition to offering traders opportunities for profit [3].

Algorithmic trading combines computer programming and financial markets [4] to execute trades at exact times. In addition to providing the best possible deal execution, placing orders immediately, and perhaps lowering trading charges, algorithmic trading [5] seeks to eliminate emotion from deals [6]. Popular trading strategies include arbitrage opportunities, trend-following strategies, and index fund rebalancing [7]. Moreover, algorithmic trading is performed either on time (time-weighted average price) or trade volume (volume-weighted average price). A computer programme will automatically keep an eye on the stock price and the moving average indicators, placing buy and sell orders when the predefined conditions are met [8]. The trader no longer needs to monitor real- time prices and graphs or manually submit orders [9]. The algorithmic trading system does this automatically by correctly identifying the trade opportunity [10].

To close deals, the most competitive pricing [11] is employed. Trade orders can be placed quickly and precisely, with a high probability of being executed at the required values. Trades are carried out promptly and at the appropriate moment to avoid major price fluctuations [12]. Reduce transaction costs [13] by having automated tests run concurrently in different market conditions. With less chance of human error while placing trades, back testing using historical and real-time data can be utilised to assess whether algorithmic trading is a viable trading strategy [14]. It lessens the possibility that human traders will make mistakes due to psychological or emotional factors. High-frequency trading (HFT) is the modern form of algorithmic trading that seeks to make money by swiftly placing several orders over a a range of decision-making variables and marketplaces depending on preprogrammed instructions [15].

The types of investing and trading operations [16] include short-term, systematic, and mid-to-long-term traders. When they don't want to affect stock prices with discrete, high- volume transactions, pension funds, insurance companies, and other buy-side firms— mid-to long-term investors—use algo-trading to acquire equities in bulk. Automated trade execution benefits short-term traders, sell-side participants, market makers (such brokerage houses), speculators, and arbitrageurs. Additionally, algo-trading helps to create enough liquidity [18] for market sellers. Pairs trading, a market-neutral trading strategy that combines a long position with a short position in a pair of highly correlated securities, such as two stocks, exchange-traded funds (ETFs), or currencies, is popular with systematic traders [19], trend watchers, hedge funds, and pairs traders.programming their trading criteria and allowing the programme to trade automatically is far more efficient [20].

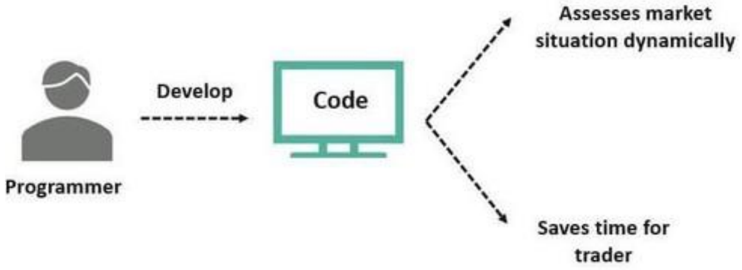

Fig. 1. Working Framework of Algorithmic Trading. Source: WallStreetMojo.

In algorithmic trading, trading strategies are implemented by algorithms that are based on procedures and regulations. It has been used far more frequently by large trading companies and institutional investors for a variety of purposes since the early 1980s. Even though algorithmic trading offers advantages like reduced costs and faster execution times, it can also amplify the market's negative inclinations by causing flash crashes and an abrupt lack of liquidity [21].

Recent advances in artificial intelligence have made learning possible—an continual process that enables programme improvement. Traders are developing algorithms based on deep learning to boost their profitability. Algorithmic trading is mostly used by institutional investors and large brokerage firms to save trading costs. According to research, algorithmic trading is especially beneficial for large order sizes, which may make up as much as 10% of all trade activity [22].

Exchanges are drawn to algorithmic trading because it streamlines and expedites order execution. Traders and investors can therefore quickly profit from little price swings. Algorithms are widely utilised in scalping trading since it involves the rapid purchase and sale of stocks at small price increments. The rapidity of order execution, usually a plus, may become a drawback when several orders are executed simultaneously without human intervention. The 2010 flash crash has been blamed on algorithmic trading. Another disadvantage of algorithmic trading is that traders may not be able to profit from price swings since liquidity, which is created by fast buy and sell orders, might disappear in an instant. It could also result in an abrupt shortage of liquidity. Studies have indicated that algorithmic trading was a major factor in the depletion of liquidity in the currency markets following the termination of the Euro peg on the Swiss franc in 2015 [23].

2. Literature Review

RQ1: Are the brokers aware of the applications of algorithmic trading?
An opportunity that can profitably be found in terms of increased earnings or cost savings is necessary for algorithmic trading. Trades are initiated based on the occurrence of favourable patterns, which are easy to apply using algorithms, without getting into the complexity of predictive analysis. Using the 50- and 200-day moving averages is a popular trend-following strategy. This demonstrates the use of a trend-following approach. By buying a dual-listed stock at a lower price in one market and selling it at a higher price in another, one might leverage the price difference as a risk-free profit opportunity or engage in arbitrage [24].

Index funds have designated times for rebalancing, which brings their holdings into alignment with their respective benchmark indexes. This creates profitable trading opportunities for algorithmic traders, who benefit from deals that are projected to yield returns of 20 to 80 basis points just prior to index fund rebalancing, depending on the number of stocks in the index fund. Algorithmic trading algorithms are used to initiate such deals in order to provide optimal prices and fast execution. Reliable mathematical models, such the delta-neutral trading strategy, allow trading on a combination of options and the underlying security. The "delta neutral" portfolio strategy compares the price change of an asset, often a marketable security, to the corresponding change in the price of its derivative in such that the assets in question have an overall differential of zero [25].

The mean reversion approach is based on the theory that the high and low values of an asset are cyclical occurrences that frequently return to their mean value, or average value. When the price of an asset moves into or out of a given price range, trading can be automated by locating, defining, and applying an algorithm based on that range. Using historical volume profiles that are stock-specific, the volume-weighted average pricing technique splits up large orders into smaller, dynamically selected portions that are released to the market.

It is recommended that the order be executed in close proximity to the VWAP, or volume- weighted average price [26]. By dividing an order into smaller, dynamically determined chunks, the time-weighted average pricing technique releases the larger order into regularly spaced time intervals between a start and finish time. By executing the order at or around the average price between the start and end timings, the goal is to minimise the impact on the market. Until the trade order is fully completed, this algorithm will continue to deliver partial orders based on the volume traded in the markets and the designated participation ratio. The associated "steps strategy" modifies this participation rate, sending orders at a user-defined percentage of market volumes, when the stock price surpasses user-defined levels [27].

The implementation shortfall approach seeks to reduce an order's execution costs while By trading on the real-time market, the implementation shortfall technique aims to minimise the expenses associated with executing an order while simultaneously capitalising on the opportunity cost of its delayed execution. The strategy will increase the target participation rate when the stock price moves in the right direction; on the other hand, it will decrease when it moves in the wrong direction. A few special classes of algorithms try to find "happenings" on the other side. Typically used by sell-side market makers, these "sniffing algorithms" are able to identify the existence of any algorithms on the purchasing side of a large order. With the use of these algorithms, the market maker will be able to identify large order possibilities and profit by filling the orders at a higher price. "High-tech front-running" is another term for this [28].

In contemporary artificial intelligence, algorithmic trading has drawn a lot of attention and is a significant topic in the financial industry. Investors, both individual and institutional, are very interested in learning more about autonomous trading algorithms that can adjust to the turbulent trading environment. The solutions that were previously suggested mainly depend on domain expertise and do not provide a useful means of dynamically modifying the trading strategy. Advances in deep reinforcement learning (DRL) have made it possible to model and solve sequential [31] real-world issues in a way that is more human-like. An innovative deep reinforcement learning-based trading agent that can benefit in erratic financial markets and make trading decisions on its own [32].

The computerization of stock trading from order book to exchange has resulted in the generation of massive volumes of real-time data. Simultaneously, the government, institutions, social media, and publicly traded firms have issued a torrent of data on the operating performance of publicly traded corporations, such as news, financial statements, and macroeconomic statistics [33]. Due to the difficulty of providing clear explanations of the interactions between the model inputs and outputs, AT refers to the use of sophisticated computer algorithms [34] to automatically make certain trading decisions in the trading cycle, such as pre-trade analysis (data analysis), trading signal generation (buying and selling recommendations), and trade execution (order management). Black box trading unnerves investors and fosters mistrust of the approach [35].

Because rules are more easily understood by humans than other data mining models and because they can produce a collection of symbolic rules that naturally express the relationship between variables, rule discovery is a crucial component of data mining [36]. Algorithmic trading, generally understood to include the application of computer algorithms for specific trading decisions, order submission, and order management after submission, is currently a popular technique among market participants. Regulators and market participants now have a pressing need to understand the effects of algorithmic trading on financial markets [37]. Market participants' actions can now be fully monitored thanks to advanced data feeds and audit trail information.

Through the establishment of asset prices and the freedom for investors to enter and exit positions in securities whenever and wherever they choose, high-quality trading markets promote capital generation and allocation. A fundamental characteristic of all kinds of algorithmic trading techniques is the identification of the underlying persistent tradable phenomenon and the creation of suitable trading chances [38]. Investors, regulators, legislators, and researchers are interested in high-frequency trading (HFT) tactics, which are a subset of algorithmic trading strategies [39]. Researchers have lately provided light on the main characteristics of HFT methods, which are now in use but mostly unknown to the general public. High-frequency relative-value trading, (1) serving as an informal or official market maker, and (2) directional trading on news releases, order flow, or other high-frequency signals are a few examples of high-frequency trading methods [40].

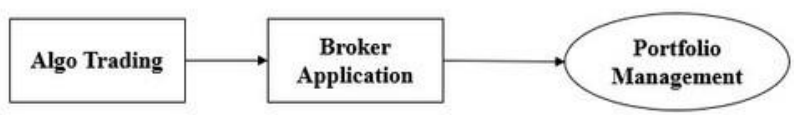

Fig. 2. Proposed Research Model.

2 Methodology and Materials

Algorithmic trading is the process of executing orders by means of automated and pre- programmed trading instructions that account for variables such as volume, time, and price. An algorithm is a set of guidelines for handling an issue. Computer algorithms are used to progressively send smaller portions of the total order to the market. By using technology in order to execute trades and track order execution, portfolio management, automated trading, real-time order placement, and the elimination of human error, the article seeks to investigate the awareness levels of brokers. 350 standardised, self-administered questionnaires were created and distributed to gather initial data on the respondents' demographics and construct (awareness) from stock brokers. The study connected to the construct (Awareness) on application of Algorithmic Trading was modified and improved upon using a 10-item scale measuring of variables [41].

Using the systematic sampling method, the main responses were gathered from the stock brokers of the NSE and BSE located within the boundaries of Bangalore district in Karnataka, India. Within the boundaries of the Bangalore district, the population consists of the top 10 stock brokers in Bangalore: Zerodha, Angel broking, Motilal Oswal, FYERS securities, India Infoline, ICICI Direct, Sharekhan, Kotak Securities, SBI Cap Securities, and Edelweiss stock brokers. A questionnaire on a five-point Likert scale was completed by 250 members of the sample. Data from the respondents was gathered using quantitative approaches. The data was examined using the Chi-Square Test, ANOVA, and Simple Percentage Analysis utilising Statistical Analysis System (SAS) software and hypothesis testing.

3 Results

Sampling adequacy supported the data validity by KMO = 0.835 > 0.70, [43], ($\chi 2 = 47.52$, $p < 0.01$), and reliability analysis confirmed strong internal consistency with Cronbach Alpha (N = 235, $\alpha = 0.90 > 0.70$, [42]). Simple percentage Analysis was conducted to understand the demographic profile of the respondents. Gender reflects that 78.51 per cent are male and 21.49 per cent female. 54.2 per cent of the respondents fall within the age group between "26–35 yrs.", 71.7 per cent respondents are aged above 36 yrs.

H 0: There is no association between the Awareness of Algorithmic trading and its application.

Table 1. Goodness-of-Fit on Awareness of Algorithmic Trading.

Variables	χ2 Value	Sig.	Result
Awareness	46.755	0.000**	Association
Real-Time Order placement	35.161	0.000**	
Tracking order execution	40.042	0.000**	Association
Portfolio Management	56.85	0.000**	Association
Automated Trading	52.75	0.000**	Association
Elimination of Human Error	30.79	0.000**	Association

A significant relationship between awareness ($\chi2$ = 46.755, N = 285, p =.00), real-time order placement ($\chi2$ = 35.161, N = 285, p =.00), order tracking ($\chi2$ = 40.042, N = 285, p =.00), portfolio management ($\chi2$ = 56.85, N = 285, p =.00), automated trading ($\chi2$ = 52.75, N = 285, p =.00), and removing human error ($\chi2$ = 30.79, N = 285, p =.00) is confirmed by the goodness-of-fit indices.

As a result, the alternative is accepted and the null hypothesis is rejected. As a result, it demonstrates that there is a strong correlation between the level of knowledge about the technology in question and how it is used by Bangalore-based stock brokers for the NSE and BSE.

Table 2. Regression Summary Statistics.

Variables	*B*	*SE of B*	*β*	*t- Value*	*p* Value
Constant	3.073	0.588	-	8.623	< 0.00
Cost	0.515	0.043	0.521	12.017	< 0.00
Tracking	0.243	0.043	0.245	5.698	< 0.00
Portfolio Management	0.577	0.029	0.611	19.731	< 0.00
Order Placement	0.266	0.029	0.283	9.128	< 0.00

The percentage of the variation in the dependent variables that the fitted sample regression equation explains is how the Coefficient of Determination R2 assesses the goodness-of-fit of the estimated Sample Regression Plane (SRP).

Table 2 displays a statistically significant regression equation (F = 333.06 p < 0.001) with an R2 of 0.894 (R2 > 0.75, Mason & Perreault, 1991). Durbin-Watson (1.981) and the fitness of indices (R = 0.901) validate the model's suitability for forecasting the predictors' automated trading. Thus, 3.073 + 0.515 (cost) + 0.243 (tracking) + 0.577 (portfolio management) + 0.266 (order placement) is the projected automated trading (Y).

Table 3. Variance Between Awareness & Decision-Making.

Decision-Making	Awareness	Mean Square	F	Sig.
Cost	Between Groups	2.301	2.046	.000*
	Within Groups	1.125		
Tracking	Between Groups	.997	.824	.000*
	Within Groups	1.210		
Portfolio Management	Between Groups	5.927	4.672	.000*
	Within Groups	1.269		
Order Placement	Between Groups	5.290	4.334	.000*
	Within Groups	1.221		
Automated Trading	Between Groups	8.239	7.112	.008**
	Within Groups	1.158		

At the one percent significance level, Decision-making and Awareness produced a statistically significant effect. Cost (F = 2.046, p < 0.001), tracking (F =.824, p < 0.001), portfolio management (F = 4.672, p < 0.001), order placement (F = 4.334, p < 0.001), and automated trading (F = 7.112, p < 0.001) are all shown to have an effect size on decision-making.

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4 Discussion, Implications and Conclusion

Fund managers frequently use trade execution algorithms, or algorithmic trading, to buy and sell enormous amounts of assets. These techniques rely on computer algorithms to identify valuable patterns and inefficiencies in the market at a frequency and pace that far exceed human capabilities.

It continuously monitors the markets and executes orders in response to the fulfilment of specific criteria, including volume, price, resistance, support, and any other factor that the trader or other market participant finds acceptable.

Algorithms are the foundation of any computer programme and all of its features [44]. Algorithmic trading outperforms discretionary trading because its rules are measurable and repeatable. An technique to active trading that is more analytical than instinctive or intuitive is provided by algorithmic trading [45].

As a result, the research study's conclusion demonstrated that stock brokers working for the NSE and BSE are aware of the aforementioned technology and that there is a higher correlation between their level of understanding of algorithmic trading and its implementation in providing stock brokerage services.

4.1 Theoretical Implications

Exchanges find algorithmic trading attractive because it facilitates quicker and simpler order execution. Traders and investors can so swiftly record profits on slight price fluctuations. Market prices can be significantly impacted by massive algorithmic trades, which can lead to losses for traders who are unable to modify their trades in reaction to these changes. Algo trading has also been blamed for escalating market turbulence and occasionally triggering "flash crashes." Algorithmic trading can beat the market if traders follow tight guidelines.

They must grasp the principles and practise prudent money management if they are to profit from algo trading. The goal of any effective algorithm trading strategy should be to reduce trading expenses while increasing trading revenues. The most common tactics include mean reversion, market timing, arbitrage, and index fund rebalancing. Among other tactics are pairs trading, scaling, and transaction cost reduction.

4.2 Managerial Implications

Algo trading is fully automated thanks to integrated technological tools, predictive models, and data analytics. Because computer-based programmes are always unbiased, traders can make faster and more balanced execution decisions without the need for human intervention. The regulations are predicated on knowledge of derivatives, probability and statistics, risk management, and historical data, among other things. The most frequent users of this more sophisticated type of trading are investment banks, hedge funds, mutual funds, and pension funds. The quoted and effective spreads both get smaller under auto quote. Due to a notable reduction in adverse selection, or the quantity of price discovery connected with trades, the spreads have shrunk.

Practical Implications

Stock market movement forecasting has been done using a variety of algorithms since the development of artificial intelligence. A mix of machine learning algorithms and statistics has been created for understanding long-term markets and projecting the opening price of the stock the following day.

Algorithmic trading, or "algo trading," is a relatively recent addition to the trading industry. Because of the complexity of algo trading, retail investors are still not allowed to participate, but institutional investors have fully dominated the market.

Algorithms are widely used by brokerage houses' proprietary desks to trade stocks, futures, and options.

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