Algorithm trading and its application in stock broking services

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Abstract. ***Purpose:*** Algorithmic trading provides a more systematic approach to active trading than methods based on trader intuition or instinct. The aim of the study is to examine the level of awareness among the brokers when integrated with technology for the purpose of executing the trades. ***Design/Methodology:*** A self-administered and structured 350 questionnaires were designed and circulated to collect the preliminary information from the stock brokers operating in NSE and BSE within the geographical limits of Bangalore district using the Systematic Sampling method to obtain a sample size of 235. Awareness, Automated trading, Elimination of human error, portfolio management, tracking order, order placement were the critical variables observed to validate the hypothesis using Simple Percentage Analysis & Chi-Square Analysis using Statistical Analysis Software (SAS). ***Findings:*** It was found that there is robust association between the level of awareness of the mentioned technology in its application by the stock brokers of NSE and BSE operating in Bangalore. Portfolio management and automated trading are the highly associated application of Algorithmic trading among the stock brokerage services. ***Originality:*** Algorithmic trading makes use of complex formulas, combined with mathematical models and human oversight, to make decisions to buy or sell financial securities on an exchange. It can be used in a wide variety of situations including order execution, arbitrage, and trend trading strategies. Algorithmic traders often make use of high-frequency trading technology, which can enable a firm to make tens of thousands of trades per second.

1 Introduction

Algorithmic trading, also known as automated trading [1], black-box trading, or algo-trading, involves placing a deal using a computer program that adheres to a predetermined set of guidelines (an algorithm). Theoretically, the deal can produce profits at a pace and frequency that are beyond the capabilities of a human trader [2]. The specified sets of instructions can

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be based on a mathematical model, time, pricing, quantity, or any other factor. In addition to providing the trader with prospects for profit, algo trading increases market liquidity and makes trading more organized by minimizing the influence of human emotions [3].

Computer programming and financial markets [4] are combined in algorithmic trading to carry out trades at precise moments. Algorithmic trading [5] aims to remove emotions from transactions, provides the best possible execution of a deal, instantly places orders, and might result in lower trading commissions [6]. Trend-following tactics, arbitrage possibilities, and index fund rebalancing [7] are examples of popular trading methods. Additionally, algorithmic trading is carried out in accordance with trading volume (volume-weighted average price) or time (time-weighted average price). When the predetermined circumstances are satisfied, a computer software will automatically monitor the stock price (as well as the moving average indicators) and place the buy and sell orders [8]. The trader is no longer need to manually enter orders or keep an eye on live pricing and graphs [9]. This is automatically accomplished by the algorithmic trading system, which accurately recognizes the trade opportunity [10].

The most competitive pricing [11] is used to complete trades. Placing trade orders is quick and precise (there is a high chance of execution at the desired levels). To prevent material price movements [12], trades are executed immediately and at the proper time. Lower transactional expenses [13] with automated tests running simultaneously on various market situations. To determine whether algorithmic trading is a feasible trading method, available historical and real-time data can be used for back testing with less possibility of human error when placing trades [14]. It decreases the likelihood that human traders would make errors based on emotional and psychological reasons. Today's version of algorithmic trading is high-frequency trading (HFT), which aims to profit from placing a lot of orders quickly across a variety of markets and decision factors based on preprogrammed instructions [15].

The forms of trading and investment activities [16] including comprises of mid-to-long term, short-term, and systematic traders. Mid- to long-term investors or buy-side firms pension funds, mutual funds, insurance companies use algo-trading to purchase stocks in large quantities when they do not want to influence stock prices with discrete, large-volume investments. Short-term traders and sell-side participants market makers (such as brokerage houses), speculators, and arbitrageurs benefit from automated trade execution; in addition, algo-trading aids in creating sufficient liquidity [18] for sellers in the market. Systematic traders [19] trend followers, hedge funds, or pairs traders (a market-neutral trading strategy that matches a long position with a short position in a pair of highly correlated instruments such as two stocks, exchange-traded funds (ETFs), or currencies) find it much more efficient to program their trading rules and let the program trade automatically [20].

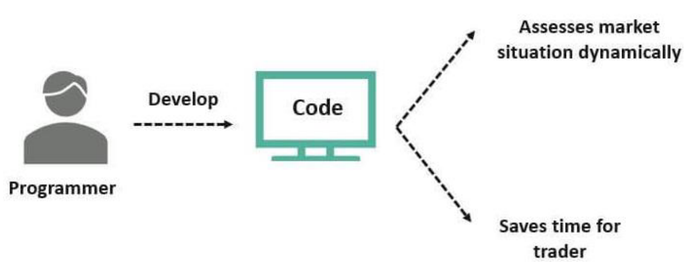

Fig. 1. Working Framework of Algorithmic Trading. Source: WallStreetMojo.

Algorithms based on processes and rules are used in algorithmic trading to implement trading strategies. Since the early 1980s, it has become much more widely employed for a range of uses by institutional investors and big trading companies. While algorithmic trading has benefits like quicker execution times and lower costs, it can also accentuate the market's unfavorable tendencies by resulting in flash crashes and a sudden loss of liquidity [21]. Deep learning, an ongoing process that allows for program improvement, has been made possible by recent advancements in artificial intelligence. To increase their profitability, traders are creating deep learning-based algorithms. Large brokerage firms and institutional investors primarily utilize algorithmic trading to reduce trading expenses. Research indicates that algorithmic trading is particularly advantageous for big order sizes, which could account for up to 10% of total trading activity [22].

Algorithmic trading is appealing to exchanges because it makes order execution quicker and simpler. As a result, traders and investors can swiftly earn a profit off little price movements. Due to the quick buying and selling of stocks at small price increments involved in the scalping trading method, algorithms are frequently used. When multiple orders are performed simultaneously without human interaction, the speed of order execution, which is typically a benefit, might become a disadvantage. Algorithmic trading has been held responsible for the 2010 flash crash. Another drawback of algorithmic trades is that liquidity, which is produced by quick buy and sell orders, might vanish in a split second, preventing traders from profiting from price fluctuations. Additionally, it may cause a sudden lack of liquidity. Research has shown that, after the Swiss franc's Euro peg was terminated in 2015, algorithmic trading played a significant role in the loss of liquidity in the currency markets [23].

RQ$_1$*: Are the brokers aware of the Algorithmic trading in terms of its application?*

The algorithmic trading requires an identified opportunity that facilitates in profitable terms of improved earnings or cost reduction. Without delving into the complexities of predictive analysis, trades are started based on the occurrence of favorable patterns, which are simple and straightforward to apply through algorithms. A well-liked trend-following tactic is to use the 50- and 200-day moving averages. This indicates the application of trend-following strategy. The price difference can be used as risk-free profit or arbitrage by purchasing a dual-listed stock at a cheaper price in one market and simultaneously selling it at a higher price in another market [24].

In order to bring their holdings into line with their respective benchmark indexes, index funds have set times for rebalancing. This generates lucrative trading opportunities for algorithmic traders, who profit from anticipated trades that, depending on the number of stocks in the index fund, give returns of 20 to 80 basis points right before index fund rebalancing. For prompt execution and the best prices, such trades are started using algorithmic trading algorithms. Trading on a mix of options and the underlying security is permitted by tested mathematical models, such as the delta-neutral trading technique. A portfolio approach known as "delta neutral" compares the change in the price of an asset, often a marketable security, to the equivalent change in the price of its derivative in such a way that the overall delta of the assets in question equals zero [25].

The idea behind the mean reversion method is that an asset's high and low values are cyclical phenomena that regularly return to their mean value (average value). Trading can be automated when an asset's price enters or exits a specific price range by identifying, defining, and using an algorithm based on that range. The volume-weighted average pricing technique divides up large orders into smaller, dynamically decided chunks that are released to the market using previous volume profiles that are stock-specific. The order should be executed in close proximity to the volume-weighted average price (VWAP) [26]. Using regularly spaced time slots between a start and finish time, the time-weighted average pricing technique divides up a large order and releases smaller, dynamically decided portions of the order to the market. The objective is to minimize market impact by executing the order at or around the average price between the start and end timings. This algorithm keeps delivering partial orders in accordance with the specified participation ratio and the volume traded in the markets until the trade order is entirely filled. When the stock price exceeds user-defined levels, the corresponding "steps strategy" raises or decreases this participation rate, sending orders at a user-defined proportion of market volumes [27].

The implementation shortfall approach seeks to reduce an order's execution costs while also taking advantage of the opportunity cost of delayed execution by trading on the real-time market. When the stock price moves favorably, the strategy will enhance the desired participation rate; conversely, when the stock price moves negatively, it will drop. A few unique classes of algorithms make an effort to locate "happenings" on the opposing side. These "sniffing algorithms" can detect the presence of any algorithms on the purchase side of a large order and are typically utilized by sell-side market makers. The market maker will be able to spot huge order opportunities with the aid of these algorithms and profit by filling the orders at a higher price. This is also known as "high-tech front-running" [28].

An innovative approach based on deep reinforcement learning (DRL) to solve the algorithmic trading problem of determining the optimal trading position at any point in time during a trading activity in the stock market. It suggests a novel DRL trading strategy to maximize the resulting Sharpe ratio performance indicator [29] across a wide range of stock markets. This new DRL approach, dubbed the Trading Deep Q-Network algorithm (TDQN), is inspired by the popular DQN algorithm but significantly adapted to the specific algorithmic trading problem at hand. The resulting reinforcement learning (RL) agent is entirely trained on the generation of artificial trajectories from a limited set of historical stock market data [30].

Algorithmic trading is an important topic in the financial market and has received a lot of attention in modern artificial intelligence. There is a strong interest among both institutional and individual investors in investigating autonomous trading algorithms that are adaptable to the volatile trading market. The previously proposed methods rely heavily on domain knowledge and lack an effective way to dynamically adjust the trading strategy. Deep reinforcement learning (DRL) breakthroughs have enabled the modelling and solution of sequential [31] real-world problems in a more human-like manner. A novel trading agent based on deep reinforcement learning that can make trading decisions autonomously and profit in volatile financial markets [32].

Large amounts of real-time data have been generated as a result of the computerization of stock trading from order book to exchange. Simultaneously, the government, institutions, social media, and publicly traded companies have released a deluge of data on the operating performance of publicly traded companies, such as news, financial statements, and macroeconomic data [33]. 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), due to the difficulty in providing simple explanations of the interactions between the model inputs and outputs. Trading with black boxes makes investors uneasy and breeds distrust in the model [35].

Rule discovery is an important aspect of data mining because it can generate a set of symbolic rules that naturally describe the relationship between variables, and rules are better understood by the human mind than any other data mining model [36]. Many market participants now use algorithmic trading, which is commonly defined as the use of computer algorithms to make certain trading decisions, submit orders, and manage those orders after they are submitted. Identifying and comprehending the impact of algorithmic trading on financial markets has become an urgent concern for market participants and regulators [37]. Advanced data feeds and audit trail information from market participants now allow for complete monitoring of market participants' actions.

High-quality trading markets encourage capital formation and allocation by establishing security prices and allowing investors to enter and exit positions in securities whenever and wherever they want. The discovery of the underlying persistent tradable phenomena and the

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generation of appropriate trading opportunities is a key feature of all types of algorithmic trading strategies [38]. High-frequency trading (HFT) strategies are a subset of algorithmic trading strategies that have piqued the interest of investors, regulators, policymakers, and academics [39]. HFT strategies exist today and are mostly unknown to the general public; however, researchers have recently shed light on their general characteristics. Several examples of high-frequency trading strategies include (1) acting as an informal or formal market maker, (2) high-frequency relative-value trading, and (3) directional trading on news releases, order flow, or other high-frequency signals [40].

The proposed research model is designed on the refined theoretical framework [41] of Deep Reinforcement Learning (DRL) where Algorithmic Trading defines and confirms its adoption and implementation by brokers leading to effective portfolio management inf financial markets. Deep Reinforcement Learning is a machine learning and artificial intelligence category in which intelligent machines can learn from their actions in the same way that humans learn from experience. The fact that an agent is rewarded or penalized based on their actions is inherent in this type of machine learning. It is a machine learning subfield that combines reinforcement and deep learning. The problem of a computational agent learning to make decisions by trial and error is addressed by RL.

Fig. 2. Proposed Research Model.

2 Methodology and Materials

The technique of executing orders using automated and pre-programmed trading instructions that take factors like price, time, and volume into consideration is known as algorithmic trading. A set of instructions for solving a problem is known as an algorithm. Smaller pieces of the entire order are gradually sent to the market via computer algorithms. The paper aims to examine the level of awareness among the brokers when integrated with technology for the purpose of executing the trades through its application in real-time order placement, tracking order execution, Portfolio management, Elimination of human error, Automated trading. A structured self-administered 350 questionnaires were designed and circulated to collect the preliminary information from the respondents, stock brokers on demographic and construct (Awareness). The 10-item scale measurement of variables were chosen for the study related to the construct (Awareness) on application of Algorithmic trading was adapted and refined [41].

The primary responses were collected from the stock brokers of both NSE and BSE within the geographical boundaries of Bangalore district in Karnataka, India, using the Systematic sampling method. The population comprises of top 10 best stock brokers in Bangalore namely Zerodha, Angel broking, Motilal Oswal, FYERS securities, India Infoline, ICICI Direct, Sharekhan, Kotak Securities, SBI Cap Securities, and Edelweiss stock brokers operating within the geographical limits of Bangalore district. A sample size of 250 responded with a completed questionnaire based on the five-point Likert scale. Quantitative methods were applied to collect the data from the respondents. The data collected was analysed using a Statistical Analysis System (SAS) software and hypothesis examination to perform the Simple Percentage Analysis, ANOVA, and Chi-Square Tests.

3 Results

Reliability Analysis confirmed excellent internal consistency with Cronbach Alpha (N= 235, $\alpha = 0.90 > 0.70$, [42]) and Sampling adequacy confirmed the data validity through KMO = 0.835 > 0.70, [43], ($\chi2 = 47.52$, $p < 0.01$).

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	$\chi2$ Value	Sig.	Result
Awareness	46.755	0.000**	
Real-Time Order placement	35.161	0.000**	Association
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

Table 1 explains the indices of goodness-of-fit obtained while examining the association between the variables of awareness and the application of Algorithmic trading among the stock brokers showed a statistical significance at 1 per cent level in their association. Chi-square statistics were used to examine the association between the categorical variables of Awareness and the application of Algo trading in terms of real-time order placement, tracking the order, portfolio management, automated trading, and eliminating human error.

The goodness-of-fit indices confirms a significant relationship at 1 per cent significance level between the awareness ($\chi2 = 46.755$, N = 285, p = .00), real-time order placement ($\chi2 = 35.161$, N = 285, p = .00), tracking the order ($\chi2 = 40.042$, N = 285, p = .00), portfolio management ($\chi2 = 56.85$, N = 285, p = .00), automated trading ($\chi2 = 52.75$, N = 285, p = .00), and eliminating human error ($\chi2 = 30.79$, N = 285, p = .00). Hence, the null hypothesis is rejected and alternative accepted. Therefore, it confirms that there is robust association between the level of awareness of the mentioned technology in its application by the stock brokers of NSE and BSE operating in Bangalore.

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 Coefficient of Determination R^2 measures the goodness-of-fit of the estimated Sample Regression Plane (SRP) in terms of the proportion of the variation in the dependent variables explained by the fitted sample regression equation. A statistically significant regression equation was found (F = 333.06 $p < 0.001$), with R^2 of 0.894 ($R^2 > 0.75$, Mason & Perreault, 1991) can be observed in Table 2. The fitness of indices (R = 0.901) and Durbin-Watson (1.981) confirm the model suitability in predicting the Automated trading by the predictors. Hence, the estimated automated trading (Y) = 3.073 + 0.515 (cost) + 0.243 (tracking) + 0.577 (portfolio management) + 0.266 (order placement).

One-Way ANOVA was conducted to compare the effect between decision-making [IVs] in determining the service [DV] depending on the awareness of algorithmic trading among the brokers. The decision-making variables are determined based on the cost, tracking, portfolio management, order placement & automating trading as illustrated in Table 3.

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		

Decision-making and Awareness yielded a statistically significant effect at a 1 per cent level of significance. The decision-making effect reflects an effect size of 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 ($F = 7.112$, $p < 0.001$).

4 Discussion, Implications and Conclusion

Algorithmic trading is to trade execution procedures that fund managers often utilize to purchase and sell huge quantities of assets. These methods rely on computer algorithms to detect market inefficiencies and profitable patterns at a frequency and pace well beyond what people are capable of. It continuously scans the markets and places orders when certain criteria, such as volume, price, resistance, or support, or any other element that the trader or other market participant is at ease with, are fulfilled. Any computer application and its features are built on algorithms [44]. Since the rules of algorithmic trading can be quantified and tested again, it performs better than discretionary trading. A more methodical approach to active trading than one relying on instinct or intuition is offered by algorithmic trading [45]. Hence, the research study was concluded that confirmed the effective level of awareness of Algorithmic trading and its application in offering stock brokerage services have stronger association and indeed the stock brokers operating for NSE and BSE are aware if the mentioned technology.

4.1 Theoretical Implications

Algorithmic trading also allows for faster and easier order execution, making it appealing to exchanges. As a result, traders and investors can quickly book profits on small price changes. Large algorithmic trades can have a large impact on market prices, resulting in losses for traders who are unable to adjust their trades in response to these changes. Algo trading has also been accused of increasing market volatility and, at times, causing so-called flash crashes. If traders adhere to strict trading discipline, algorithmic trading can outperform the market. To benefit from algo trading, they must practice effective money management and understand the fundamentals. Any good algorithm trading strategy must aim to increase trading revenues while decreasing trading costs. Arbitrage, index fund rebalancing, mean reversion, and market timing are the most popular strategies. Scalping, transaction cost reduction, and pairs trading are some other strategies.

4.2 Managerial Implications

With integrated technology tools, predictive models, and data analytics, algo trading is completely automated. Because it does not require human intervention, traders can make faster and more balanced execution decisions because computer-based programs are always unbiased. The rules are based on factors such as derivatives knowledge, statistics and probability, risk management, and historical data. Hedge funds, mutual funds, pension funds, and investment banks are the most common users of this more advanced form of trading. Under auto quote, both quoted and effective spreads narrow. The narrower spreads are the result of a significant decrease in adverse selection, or the amount of price discovery associated with trades.

4.3 Practical Implications

Since the advent of artificial intelligence, numerous algorithms have been used to forecast stock market movement. For comprehending long-term markets or projecting the stock's opening price the next day, a combination of statistics and machine learning algorithms has been developed. Algorithmic trading, also known as algo trading, is a relatively new product on the market. While retail investors are still excluded from algo trading due to the complexities involved, institutional investors have completely taken over algo trading. Even proprietary desks at brokerage firms use algos extensively to trade equities, futures, and options.

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