YUGATO

ISSN: 0387-5695, eISSN: 0387-5695
Vol. 76 No. 1 (2024)

Received: January 13, 2023 / Revised: January 29, 2023 / Accepted: February 27, 2024 / Published: March 22, 2024

ANALYZING THE IMPACT OF HUMAN INTELLIGENCE OVER ALGORITHMIC TRADING: A CONTEXTUAL STUDY WITH VAR MODEL

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Abstract

In today's world, algorithms control everything, including machine-driven sectors like the stock market. This paper examines how algorithmic trading systems impact the value-at-risk model, helping investors with informed fund allocation and risk management. This research focuses on the impact of human decision-making on the Algorithmic Trading with Value at Risk model and investigates the challenges and opportunities of algorithmic trading for individual investors. The study aims to evaluate the role of human intelligence in algorithmic trading strategies applied to Value at Risk models. By analyzing the interaction between human decision-making and algorithmic systems, the research aims to uncover how traders navigate the changing landscape, emphasizing the implications for risk management and investment strategies. Additionally, it analyses the correlation between algorithmic trading and value at risk using primary data, followed by an analysis of the relationship between value at risk and human intelligence. Although algorithmic trading is dominant in guiding investment decisions, human intelligence remains indispensable at every stage of the machine's operation.

Key Words: Algorithmic Trading, Value-at-Risk model, Human Intelligence, Financial Decision, Risk Mitigation, Technology Integration.

1. Introduction

In recent years, there has been a significant shift in the focus of commerce and management towards the integration of advanced technology like machine learning and artificial intelligence. This integration has resulted in a tremendous transformation, particularly in the financial services sector. The rise in popularity of algorithmic trading can be attributed to the availability of data and technological improvements. This technique is based on the analysis of technical indicators, market data, and sentiment analysis of news. One subgroup is high-frequency trading, which entails making big deals quickly. This strategy can improve trade efficiency, lower transaction costs, and increase market liquidity [1]. Increasingly predictable and uncertain foreign currency trading markets are primarily predicted by algorithmic trading. However, with predictable patterns, uncertainty is on the rise, and more complex sub-sequences are generated as a result of algorithmic participation. At the fifth digit, further ambiguity is observed[2]. The financial sector is generally enabled to flourish through technology adoption, with computer science being the root of algorithmic trading, which is an integral part of computerized trading platforms.

Predictable but uncertain forex markets are created by algorithmic trading. With algorithmic participation, complexity and ambiguity are increased[3]. A significant turning point was marked in India and other nations during the 1990s with the emergence of electronic exchanges and trading systems. The current research direction is to formalize algorithmic trading within a framework of reinforcement learning, with an emphasis on improving reward engineering, expanding the observation space, and loosening limitations to meet Sharpe ratio goals[4]. The advancement of algorithmic trading has been driven by a range of technologies, from traditional floor trading to electronic platforms. This has been propelled by High-Frequency Trading (HFT), which emerged in the 2000s, leading the way for algorithmic trading. HFT utilizes powerful algorithms and collaborative services to execute transactions at lightning speed, providing real-time transactions and forecasting capabilities. Algorithmic trading has a significant impact on both Wall Street and Main Street, and it is a major factor in financial technologies and services. A culture of open communication, information sharing, and teamwork is required for algorithmic trading methods to be flexible and transparent[5]. High-level assurance can be provided by automated testing. The size and scope of automated control systems in algorithmic trading organizations are varied, and Scharre's recommendation for complete integration is not always followed. The principles of High-Reliability Organisations are crucially dedicated to event mitigation in an organization[6]. Despite the growth of technology, an advantage is still maintained by Human Intelligence in terms of creativity, innovative thinking, and problem-solving skills, particularly when it comes to trading strategies. The dynamics of liquidity supply and demand are impacted by algorithmic traders and the way they employ technology to reduce the friction associated with monitoring. It has been found that algorithmic traders lower liquidity volatility by consuming cheap liquidity and providing expensive liquidity. The research indicates that these traders play a crucial role in maintaining the balance of liquidity supply and demand in the market[7].

Algorithmic trading, which is also referred to as automated trading or algo trading, has been increasingly popular as a trading strategy in recent years. To save transaction costs, an intraday trading algorithm is created to absorb price shocks during online portfolio selection rebalancing deliberately. Market orders are split effectively and costs are reduced by utilizing real-time limit order book data, particularly in situations where market liquidity is constrained[8]. The analysis and prediction of market data are harnessed by algorithmic trading systems at a speed that surpasses that of human traders. These systems consist of statistical analysis, mathematical models, and a predefined framework to identify trading opportunities and automatically execute trading orders.

Trade facilitation in markets that use a limit order book system is supported by market players who submit market or limit orders. The success of market-making tactics is derived from the alternating buy and sell orders that market makers use to provide liquidity, particularly to those willing to cross the bid-ask spread[9].It is indicated by the analysis that economic value can be maintained by the optimized trading algorithm, even in the presence of frequent signals, due to the surplus profits generated by the pandemic and the comparatively low transaction costs in commodity trading [10]. Algorithmic Trading is defined and the Order-to-Trade Ratio is utilized as an efficiency metric in this study. The unfavorable impression of Algorithmic Trading in the Indian stock market is refuted and a more equitable acknowledgment of its beneficial effects on market quality is promoted[11]. The dual impact and implications of algorithmic trading, particularly in the context of high-frequency trading, have been under scrutiny. A significant portion of global financial activities is accounted for by algorithmic trading, which is recognized for its growing popularity and role in price discovery, market depth analysis, and overcoming challenges in executing large orders [12].

Various methods are employed in algorithmic trading, such as trend following, mean reversion, market making, and statistical arbitrage. To detect structural breakdowns in time series, an analytic approach is utilized that assumes stable variance up until a breakpoint, and then iteratively identifies the breakpoints[13]. The processing of vast amounts of market data, including price feeds, order books, and other related data, to make informed trading decisions is known as algorithmic trading. Algorithmic trading offers a new level of efficiency and precision to trading, with the potential to generate greater returns. Recent research has focused on improving algorithms for managing large-scale portfolios, with particular attention given to customized decomposition techniques for the formulation of piecewise constant management fees and specific interior-point techniques for continuous management fees[14]. It is worth noting that algorithmic trading is associated with certain risks that necessitate a thorough understanding of its underlying principles and processes. Furthermore, optimal outcomes require careful monitoring and risk management. Wittgensteinian language game theory is used to investigate unintended consequences in automated financial systems. It is proposed that algorithms perform acts through language, which can be utilized to mitigate risks[15].

Lucrative strategies for continuous futures contracts are created through the use of learning algorithms such as Advantage Actor-Critic, Policy Gradients, and Deep Q-learning Networks, in the process of strengthening algorithmic trading[16]. The importance of sentiment and technical analysis indicators is increasingly recognized in the field of algorithmic trading research. In this study, the benefits of merging these features are investigated using two different genetic programming methods[17].Efficiency and reliability in financial trading can be improved through algorithmic trading, which utilizes forecasting and arbitrage. Deep learning-based algorithmic trading models have been extensively researched to enhance trading forecasting and analysis [18].

The effects of algorithmic trading on online peer-to-peer lending markets were investigated in a study, which revealed that institutional investors may dominate the market, leading to a possible exclusion of individual investors. The study showed that the recent Application Programming Interface upgrade on Prosper.com may have expanded the market for slightly lower-quality loans, while simultaneously pushing out individual "manual" investors from high-performing loans [19]. An ensemble of regression algorithms and a dynamic asset selection strategy that eliminates underperforming assets based on historical performance are used to explore a general algorithmic approach. The instance, applied to the S&P 500 Index, uses statistical arbitrage as a trading strategy and forecasts intra-day returns using a combination of Random Forests, Support Vector Machines, ARIMA, and Light Gradient Boosting[20]. By adding technical indicators and employing an enhanced Split Feature Space Ensemble Method through deep reinforcement learning, the Standard Ensemble Method for algorithmic trading has been improved as demonstrated in the study. Promising outcomes have been shown in terms of Sharpe ratio, maximum drawdown, and yearly return[21].

Human Intelligence.

The cognitive process and thinking ability that distinguish humans from other species is represented by human intelligence. It plays an important role in solving both personal and external problems and includes a wide range of skills such as perception, memory, language comprehension, attention, logical reasoning, and emotional intelligence. Despite the prevalence of machine learning, chatbots, and artificial intelligence, human intelligence continues to be a vital tool for problem-solving and innovation. It is a combination of emotional and social abilities that contribute to human progress. Overall, human intelligence is a unique and multifaceted quality that is essential for tackling complex challenges.

Problem of the Study

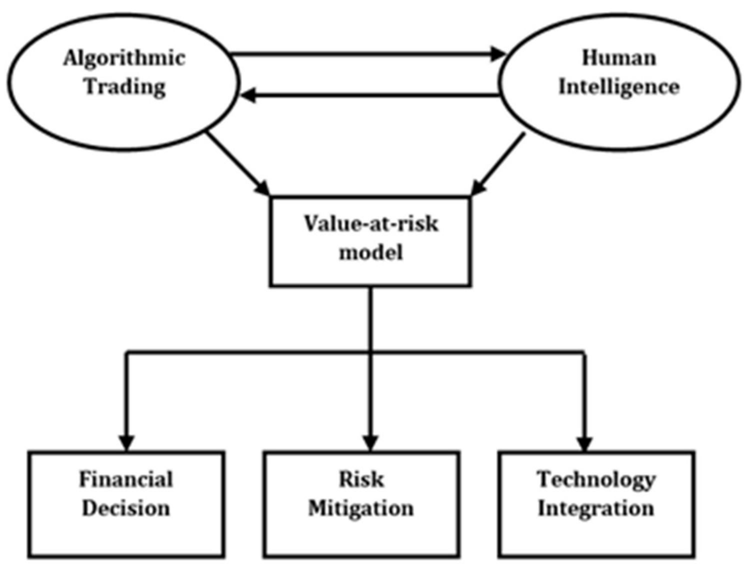
The financial landscape has been reshaped by the advent of algorithmic trading, which has led to trades being executed at unprecedented speeds using computer algorithms. This has raised an important question: How much is algorithmic trading trusted by investors compared to human intelligence when it comes to financial decision-making and risk mitigation? In this study, the reliability of algorithmic trading results is being assessed, as it is a crucial concern for investors, financial institutions, and regulators. It is essential to understand this trust dynamic to ensure the stability and integrity of financial markets.

2. Materials & Methods

4.1 Data Collection & Methodology

A total of 109 samples were collected from different stock market participants using Google Forms as part of the data collection process. Furthermore, secondary data was gathered from various articles and textbooks regarding the trading practices and stock market expertise of the investors. The statistical tool used was the one-sample t-test, which is designed to determine whether the mean estimated from sample data obtained from a single group differs from a predetermined value set by the researcher.

Opportunities can be identified faster by using machine learning models and algorithms in algorithmic trading to automate trading decisions. However, human intelligence is still essential for strategic decision-making, trade parameter setting, and oversight. Financial risk can be estimated and managed using Value-at-Risk models. Financial decision-making involves analyzing market data to determine investment strategies, portfolio allocation, and risk management. Reliable technology infrastructure, including data storage, high-speed computation, and APIs, is crucial to both models. When these technologies are seamlessly integrated into a comprehensive framework for financial decision-making, returns can be maximized, and risk can be effectively managed.



4.2 Scope of the study

The integration of Value-at-Risk, algorithmic trading, and human intelligence in financial decision-making and risk mitigation is investigated in this study. The impact of technology, specifically algorithmic trading systems, on risk assessment and management within Value-at-Risk models is explored. The role of human intelligence in guiding algorithmic trading strategies and its impact on risk mitigation efforts is examined, alongside the implications of cognitive biases. Furthermore, the study explores how technological advancements are driving the integration of algorithmic trading and human intelligence to enhance decision-making accuracy and efficiency in mitigating financial risks.

4.3 Objectives &Hypothesis testing

4.3.1 Objectives:

To Compare the intervention of Human Intelligence in algorithmic trading and Value-at-Risk. To examine the opportunities and challenges of algorithmic trading from the viewpoint of individual investors, as well as to assess the implications of Algorithmic trading among investors.

4.3.2 Hypothesis

H0: There is no Significance difference between the type of Algorithmic trading and its impact on financial decisions, Risk Mitigation, and Integration of Technology by the Investor.

H1: There is a Significance difference between the type of Algorithmic trading and its impact on financial decisions, Risk Mitigation, and Integration of Technology by the Investor.

4.4 Statistical Analysis

Statistical significance was analyzed by taking three major areas and One Sample T-test was conducted using SPSS Version 27 and the statistical significance given is $*P<0.05$.

3. Result

Objective 1: To Compare the intervention of Human Intelligence in algorithmic trading Value-at-Risk.

Algorithmic trading has gained immense popularity among investors, stock brokers, and portfolio advisers. It is an efficient tool used to study patterns in the stock market and mitigate risks. The Value-at-Risk (VaR) model is considered the foundation for all risk models and tells the potential losses an individual can bear. Although this model has become outdated, it is still used for the stop-loss process. Several VaR models are available, such as Variance-covariance VaR, Delta-Normal VaR, CVaR (Conditional VaR), Parametric VaR, Non-Parametric VaR, and many more. However, Historical VaR, Monte Carlo simulation, and Variance-Covariance VaR models are predominantly used. Practical applications utilize VaR, and each individual uses it to measure the risk. Several tests are included in the suggested method for estimating and testing multi-scaling in financial time series using Monte Carlo MRW simulation. The tests are designed to distinguish between weak and strong multi-scaling, while also addressing the effect of anomalies on scaling exponents. The method is effective in reducing errors in Value-at-risk forecasting [34]. It has been indicated by simulations that an increase in the level of disagreement among market players leads to higher volatility of prices, greater deviation from the unaffected market price, and more frequent trading [35].

A flexible and relevant solution, Conditional Value at Risk can be applied to various problem domains, such as project management and budget allocation, where unpredictable outcomes need to be handled effectively [36]. A single quantitative measure of potential losses over a specific time frame is derived by combining various components of price risk in Value-at-risk models. The market risk of a financial asset portfolio is then calculated using this measure [37]. Value at Risk is utilized by Microsoft as a management tool to estimate the company's exposure to market risk, and the estimated figures are reported in its reports. To eliminate the requirement for copula functions, the Encoded Value-at-risk model automatically introduces regime shifts and seasonality effects through a normalization technique. This allows for swift modifications to risk projections during financial crises[38]. This study aims to investigate and compare the use of value-at-risk modeling and human intelligence in algorithmic trading. In today's fluid and data-rich financial markets, both human skill and artificial intelligence play a significant role. The complex interactions and contributions of human decision-making with cutting-edge computational tools in the fields of trading and risk management are the driving forces behind this work.

The objective is to utilize algorithmic trading strategies to optimize the returns of a portfolio that comprises five different stocks - Stock 1, Stock 2, Stock 3, Stock 4, and Stock 5. The buy and sell decisions for these stocks are made using trading algorithms and historical data. Algorithmic trading involves analyzing past price changes, trade volumes, and other data relevant to each stock to make trading decisions. Trading decisions are made automatically and quickly by leveraging computer power and historical data to maximize the portfolio's profitability. Additionally, the risk associated with the portfolio is better understood by calculating Value-at-Risk. This is a risk management metric that estimates the potential loss in portfolio value at a specific level of confidence over a given time horizon. To better understand the risk associated with the portfolio, the Value at risk will be calculated using the assumed value. The formula for a parametric Value at risk calculation for a portfolio is used:

$$VaR = \mu + z \cdot \sigma \quad (1)$$

The calculation of Value-at-Risk involves the estimation of the potential loss in the value of a portfolio, given a certain level of confidence. To calculate the 1-day Value at risk with a 95% confidence level (Z = 1.645), assuming an expected portfolio return of 0.2% per day (μ) and a standard deviation of 1.5% per day (σ), these values would be plugged

into equation 1. The formula for Value-at-Risk calculation includes the expected portfolio return (μ), the z-score corresponding to the desired confidence level (Z), and the standard deviation of the portfolio's returns (σ).

$$Value\ at\ Risk = \mu + z \cdot \sigma$$

Value-at-Risk = 0.2% + 1.645 * 1.5%

Value-at-Risk = 2.47%

Portfolio managers can estimate the potential losses that may occur from algorithmic trading strategies. Typically, under normal market conditions, the portfolio may lose up to 2.47%. However, it is essential to note that there is a 5% chance that the portfolio could lose more than 2.47% of its value in one day. Combining Value-at-Risk with algorithmic trading enables portfolio managers to evaluate and manage risk actively. By using computational analysis and historical data, portfolio managers can make defensible decisions to maximize returns while maintaining acceptable risk levels. Risk-based strategies are being incorporated into energy management models lately to handle parameter uncertainty. Notably, to assess investment risk, some research has used the value-at-risk concept, which is widely used in economics [39].

i. To examine the opportunities and challenges of algorithmic trading from the viewpoint of individual investors, as well as to assess the implications of Algorithmic trading among investors.

The objective of this study is to examine algorithmic trading and its opportunities and challenges from the perspective of various types of investors, including individual investors, portfolio advisors, and stock brokers. Primary data was collected from different investors to analyze their objectives. It was found that algorithmic trading was used by 33% of the respondents to manage market volatility, while 39.4% were confident that algorithmic trading strategies could outperform human traders in terms of profitability. However, it was believed by 37.6% of the respondents that the use of algorithmic trading contributed to market instability and price fluctuations. To support the objective, the types of investors using algorithmic trading, financial decisions being made through algorithmic trading, and how risks associated with algorithmic trading can be mitigated were focused on in this study.

Table 1: Table showing the output of one sample Statistics.

One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
Types of Traders	109	1.58	.761	.073
Financial Decision	109	3.23	1.191	.114
Risk Mitigation	109	3.06	1.201	.115
Technology Integration	109	3.21	1.123	.108

Table 2: Table showing the output of one sample T-Test

One-Sample Test					
	Test Value = 0				
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference
					Lower
Types of Investors	21.641	108	.000	1.578	1.43
Financial Decision	28.302	108	.000	3.229	3.00
Risk Mitigation	26.567	108	.000	3.055	2.83
Technology Integration	29.858	108	.000	3.211	3.00

The one-sample T-test, as shown in Table 1, is a statistical tool that is used to test hypotheses and determine if the mean of a single sample of data is significantly different from a hypothesized population mean. It is often used when a sample of data needs to be assessed as representative of a large population or if it shows a statistically significant deviation from the population mean.

In this analysis, types of investors were considered as population means, and financial decision-making, risk mitigation, and technology strategy were considered as individual means. After the analysis was conducted, as shown in Table 2, it was found that all the entities such as financial decisions, risk mitigation, and technology integration had two-tailed significance values of less than 0.05, providing a confidence level of 95%.

Since the significance levels of all the entities were less than the standard significance value, the null hypothesis can be rejected, and the alternate hypothesis can be accepted, which states that there is a significant difference between the type of Algorithmic trading and its impact on financial decisions, risk mitigation, and integration of technology by the investor.

As per the hypothesis, a significant difference is justified between algorithmic trading and financial decisions based on human intelligence and risk mitigation through the integration of technology. If there is no significant difference between algorithmic trading and human intelligence, then algorithmic trading or automated trading processes would not be used. Complex code or machine learning would not be required either.

4. Discussions

In financial research, Algorithmic Trading and value-at-risk models have gained significant popularity, but there is still much to learn about combining these two essential elements. This study aims to explore the synergy between algorithmic trading strategies and Value at Risk models to improve risk assessment and fill a significant gap in the literature. It is crucial to understand how the interaction between algorithmic trading and human intelligence continues to change the market's nature. The goal of algorithmic trading techniques is to automate financial trading decision-making procedures, considering the complexity of stock price decisions that arise from a variety of circumstances. These computer-based decisions can resolve the continuous difficulty faced by analysts and investors, dynamically reacting to fluctuations in price [22]. Trading agents are created through statistical analysis and historical data in automated low-frequency quantitative stock trading, with minimal human involvement [23]. Algorithmic trading strategies typically involve the use of mathematical models, statistical analysis, and automated execution to make trading decisions [24]. The impact of news analytics on financial markets, specifically algorithmic trading, is being studied. The market responses to news stories of similar nature are being compared, irrespective of the actual content of the news, to analyze their influence [25].

The interaction between humans and models in algorithmic trading is analyzed in this research, with a specific emphasis on the influence of machine learning algorithms on trading and investment management. The study aims to bring clarity to the impact of machine learning algorithms on trading and investment management by examining the interaction between models and humans [26]. A trading system has been proposed that utilizes a genetic algorithm to modify indicator parameters. These parameters are then incorporated into a neural network to optimize the system based on different market types [27]. It is widely acknowledged that algorithmic trading platforms are superior to human traders, as they can integrate and analyze vast amounts of big data. However, these systems must be monitored by regulators to ensure their compliance with regulations and ethical standards[28]. Automated, pre-programmed rules are utilized in algorithmic trading to execute orders. This method enhances strategy development, testing, and execution procedures, resulting in improved success rates and better risk management[29]. The growth of computing power in high-frequency trading has been examined in the literature, with a focus on the crucial role played by algorithms. It has been found that algorithms are more efficient than their human counterparts and have the potential to maximize benefits and remove market inefficiencies[30]. High-frequency trading and analysis of large datasets can be managed by AI systems. Machine learning and deep learning algorithms are now used for financial forecasting. The majority of studies conducted have demonstrated the effectiveness of these systems. It is necessary to adapt algorithmic trading systems to certain market circumstances and risk scenarios. With innovative approaches, algorithmic trading systems have a bright future[31]. A challenge is posed for Artificial Intelligence in implementing efficient high-frequency automated trading systems in the Forex Exchange Market. This involves computing all possible outcomes of controllable system components affected by random price fluctuations, using a semi-generative configuration[32]. In the study, a novel theorem based on Stochastic Differential Equation has been presented for Bi-Directional grid trading. It has been emphasized that the impact of profit factors and grid width on equity is minimal in the short term. The primary factor that influences system profitability is the interaction between drift and diffusion. It has been suggested that good profit may be yielded by human intervention[33].

5. Conclusion

Algorithmic trading is considered a well-liked method for gauging market volatility and reducing risk in the stock market, while Value-at-Risk is regarded as the best instrument for calculating financial risk, establishing risk boundaries, and assessing performance. It is believed by 34.9% of respondents that market efficiency and liquidity can be improved with algorithmic trading, which is also thought to affect market behavior. Technologies that combine artificial intelligence with algorithmic trading systems are being invested in by trading firms and professionals to enhance algorithmic models, trading methods, risk assessment, and adaptability to market conditions. Combining algorithmic trading with human intelligence can help with comprehensive analysis, precise market projections, and ethical standards. Market projections can be aided by real-time human intervention and interpretation of investor behavior. It is believed by some investors that greater profits can be produced through the use of human intelligence, including feelings, intuition, and experience.

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