Allana Management Journal of Research (AMJR) Vol.15 (02). pp 054 - 061, Dec 2025
Available Online at ***https://theaimsjournal.org***
DOI: https://doi.org/10.62223/AMJR.2025.150206
ISSN NO: 2581 – 3137

Assessing the impact of algorithmic trading on Indian stock market and stakeholders in the era of high-frequency trading – An ISM approach.

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ARTICLE HISTORY

Received on: 20/10/2025
Accepted on: 01/11/2025
Available Online: 28/12/2025

Key words:
Algorithmic trading, high-frequency trading, trading strategies, back testing, big data, artificial intelligence.

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ABSTRACT

Algorithmic trading has rapidly transformed the functioning of modern financial markets, particularly in emerging economies like India. This study explores how algorithmic trading influences market performance and stakeholders, offering a structured framework to understand its growing significance in the Indian stock market.

Purpose: The major purpose of this research paper was to understand the relationship between algorithmic trading and its impact on the stakeholders in the Indian stock market. This paper focuses on various factors of algorithmic trading, their impact on performance, and how popular it has become in recent times

Design/Methodology/Approach: This research comprises of primary data and secondary data. In this paper, researchers have also presented a theoretical framework for understanding and analyzing the use and impact of algorithmic trading by using Interpretive Structural Modeling (ISM) to develop an inter-relationship that will provide the right direction to researchers for further research.

Findings: Algorithmic trading strategies and big data and artificial intelligence. Also, Algorithmic trading strategies and high frequency trading are very important aspects for each other because if we use algorithms for high frequency trading it would increase liquidity and improve efficiency in trading. By using the ISM modeling technique, researchers got three levels based on hierarchy. The output suggested that the variables in the level 2(High Frequency Trading, Big Data and Artificial intelligence) level 3(Back testing ability, Diversification of trades) are considered as the most important factors to assess the impact of algorithmic trading on Indian stock market and stakeholders in the era of high-frequency trading.

Research Limitations/Implications: The study was conducted by using an interview method and expert opinion was collected from 30 experts from the finance domain. The study was limited to 30 experts so limited variables we considered for the ISM model. The application of this in the real world would require some modifications.

Originality/Value: It's the first time a conceptual model has been proposed by researchers for assessing the impact of algorithmic trading on Indian stock market by using ISM.

INTRODUCTION

The importance of stock market is felt all around the world in different phases ranging from stock market crash in the USA in the year 1932 to the Harshad Mehta scam in the Indian stock markets (Ramkumar, 2018). Over the years the Indian financial market has seen a tremendous change from the physical share trading to electronic trading and technology getting increasingly involved in the financial markets.

While using technology in the right way it can minimize the losses and maximize the returns and adhere to the changes in financial sector that is algorithm trading. Algorithmic trading and high frequency trading and becoming the buzz words as it is being widely used all over the world. Apart from the Indian stock market (Breckenfelder, 2013) analyses the NASDAQ OMXS 30 index and he found that there is a very tough competition among the high frequency trading firms, and this induces more liquidity in the market. According to (Chaboud et al., 2014), As evaluated by the frequency of triangle arbitrage possibilities and the auto correlation of high frequency returns in Indian stock market as well as foreign stock markets, algorithmic trading is related with higher price efficiency. An analysis done by (Boehmer, Fong, & Wu, 2012) of 42 equity markets showed that at volatility increases in the short term when the algorithm intensity rises. In this paper, the researchers also indicate that an increase in volatility cannot be linked to speedier price discovery or algorithmic traders' for entering risky markets.

Many studies have been able to identify in the field of algorithmic trading and high frequency trading but none of them have been conducted to identify the impact of it on small stakeholders as well as retail individuals and this study also covers the difficulties faced by them while adopting algorithmic trading in the era of high frequency trading. This study is done to understand the phenomenon of algorithm trading, its operational efficiency, and the effect of high frequency trading on price volatility. This paper will also focus on various factors such as algorithmic trading strategies, price volatility, high frequency trading, back testing ability diversification of trades and big data and artificial intelligence.

LITERATURE REVIEW

Algorithmic Trading Strategies Momentum investing -

In finance momentum means the change in speed and direction of an asset in the market in relation to its price. It is a kind of investing strategy where one analyzes the assets for a short period and buys when the prices are rising (Quantinsti,2021). It can be for an upward trend as well as a downward trend. Momentum investing means if a stock is in the direction for and upward momentum may be because it is trending or may be that the commodity cycle has just kicked in say for example recently the steel and metal industry was in a boom so the momentum of all stocks in the steel and metal industry might go up and you remain invested only till the momentum lasts. You buy and sell when the momentum is over. This can also happen in the reverse case, for example government announces an increase in tax rate for the Auto sector and the stocks of that industry might go on a downward trend. Some of the evidence in the academic research implies that momentum investing exists in the market from a long time even before researchers studied on them (Frazzini, Israel, & Moskowitz,2014). For a simple momentum strategy, the algorithms analyze and identify moving averages, *stochastic oscillator* as well as the relative strength index (RSI). The two moving averages used by the algorithms to analyze the trends are the 50- and 200-day moving average (Medium,2021). A lot of people might catch a negative momentum, and they start to short sell the stocks and thus make a profit out of it.

Statistical Arbitrage

Statistical Arbitrage aims to acknowledge cost differentials that are considered in various markets or between assets, which make recognised and predictable links with one another. Also arbitrage strategies try to use a slight change in prices in these tools, whether it is under or over judgement.

Performance based

Execution-based plans are an example of an algorithmic trading approach. These are the kind of techniques that institutional investors will use when making large-scale purchases. These tactics employ a variety of methods to acquire the most secure investment feasible. Algorithmic traders mostly earn profits by using intraday strategies and timing the market performance by analysing one minute time frame. This strategy is popular among intraday traders (Syamala & Wadhwa, 2020). One can also use the methodology of (Carrion, 2013) in which he uses Volume Weighted Average Price which is also known as VWAP analysis to measure the performance of traders who popularly use algorithms. As per the findings by Syamala & Wadhwa, (2020) of algorithmic trading for stocks listed on NSE they used VWAP analysis and documented those algorithmics are very helpful in timing the market and its performance for longer time durations as compared to a shorter time.

HIGH FREQUENCY TRADING

Increase's liquidity

A algorithm which is developed can help one to trade faster as it can execute trades within a fraction of a second without any interference by a human and this is the main reason why many traders are adopting the algorithmic trading strategy. There is a misunderstanding that by using algorithms it may lead to more volatility, and it may also lead to price disruptions. Research has also proved that using algorithmic trading it reduces the transaction cost, and it provides liquidity (Moneycontrol, 2020). High frequency trading (HFT) adds liquidity to the markets, which is very necessary for its functioning. Liquidity is generally the difference between the buying and the selling prices. There are other factors as well which measure the liquidity, and they include the time taken for a trade, the total turnover, and the turnover ratio (NIFM, 2017). The main advantage of high frequency trading is that it has increased liquidity in the market and reduced the difference between bid-ask price that were excessively small (Investopedia,2021).

Increase Efficiency

By reducing the transaction costs high frequency trading increases productivity in the market. The speed at which financial markets integrate new information into asset values is known as market efficiency. HFT's higher trading velocity assures that market prices respond more swiftly to fresh information. In HFT the bandwidth as well as the location of servers plays a very important part and hence, they are placed where the exchanges are established which allows traders to be right next to them (Rajalakshmi, 2018). The co-location of stock exchanges allows a faster interception between two servers by which traders can trade faster but then in this case the small traders are at a disadvantage (Lal, 2015). A theory suggests that HFT can have both positive as well as negative contributions. The positive contribution is that it transmits information quickly thereby improving the liquidity in the market (Menkveld & Jovanovic, 2010). The negative contribution is that it leads to increase in selecting costs for existing non algorithmic traders which can have negative externalities (Cartea & Penalva, 2012).

Higher Returns for Investors

Returns to investors are reduced by transaction costs. By reducing the transaction costs, it leads to a higher return for the investors. Lastly reducing the transaction cost will lead to a continuing increase in the price of an asset and will also lead to and increasing portfolio value.

Back testing ability
Filtration

Earlier traders had no idea whether their algorithm strategy would work or not. But now algorithms can run on past data to see whether them yield the correct results. Once they reach a right level then they can be applied in the real world (Dell Technologies, 2020). Under the back testing strategy, the first step is filtration. To ensure that we get a successful trade one must filter out certain strategies that do not meet our criteria. Back testing gives us an option to filter mechanism because it allows us to eliminate techniques that do not fulfil our requirements.

Modeling and Optimization

After filtration, the next step would be modeling and optimization which would enable us to test new models. It helps us to put new models to the test which would work in the market. By optimizing the strategy by changing values also helps us to recalculate the performance. Back testing is very useful in testing algorithms, but it does not allow to use that how this strategy will work in the future, as the key advantage is in understanding the strategy through a simulated experience with real-world conditions from the past (Philip, Michal & Vidhi, 2013). The trading world is huge and there are variety of trading systems that analyze by taking several technical indicators into consideration that focus on estimating and utilizing a window size for back testing (Vezeris et al., 2019)

Verification

After successfully filtering and optimizing the final step in back testing would be to verify and ensure that the strategy has been implemented correctly. In some cases, we may also use external strategy signals, and we will frequently have access to indicators like Sharpe Ratio and Drawdown characteristics and as a result we will compare it with our own implementation.

After running a successful back test, we get a back testing report which includes the maximum gains, losses, average gain per trade, average loss per trade, and much more. These metrices also give a detailed picture about the performance of the algorithm. There are several websites that let you use algo trading and Streak by Zerodha is one of them which allows you to create an algo, back test it and then deploy it live in the market. It is very easy and simple to use and can create an algo within minutes. After successful back testing one can deploy the algo on one click actionable notification by which users can enter and exit their positions (Gunjan, 2019).

Big Data and Artificial intelligence - Need for simpler tools

According to Datacamp, (2020), "Artificial intelligence is a process where the software accomplishes something by what we would consider as an intelligent act. And intelligence can be defined to accomplish a definite goal." Artificial intelligence combined with finance would be a great combination as it has a forward-looking approach and would save time and make our work more productive. Using AI in making trading algos are better at predicting the market and it leads to generating more profit (Hilbert & Darmon, 2020). It is a model for simulation that begins at a point in time and expand into the future. Using python as a language for automated trading can be a great tool for it. With advance strategies being implemented by using programming skill algorithms can harness complex models, computations, statistics, by using artificial intelligence to transact at a faster speed measured in microseconds (Yadav, 2015). Today, having the right tool for algorithmic trading is very essential.

Lowering barriers to entry

Learning how to use these programs can even help you to trade faster and more with individuals and companies are making heavy investment in technology which will enable them to trade faster than ever before. Building various models, learning various tactics that involve algo trading and monitoring it can be very helpful when markets are not performing well. For the near future, human involvement and keeping a track of these algorithms will be needed (Joyce, 2020). Today, individuals can opt to skip to learn coding as there are applications already built which lowers the barriers to use algorithmic trading. Artificial Intelligence has become all-pervasive in the industry because of technological advancements. In the Finance industry, both developed and emerging markets have adopted this technology (NIFM Report, 2017).

Diversification of trades

Multiple trades at one time

Algo trading allows investors to perform several trades and trading methods simultaneously, which is not possible with manual transactions. As a result, trading opportunities across several markets and securities can be scanned and performed at the same time. As a result, Algo trading in India enables investors to benefit from diversification, which is tough to do in traditional trading. Having numerous trades open at the same time can sometimes spread risk rather than increase it, and there is some logic to this argument. However, it is crucial not to mix up trading and investing (capital, 2019).

RESEARCH METHODOLOGY

The study of this research paper was done by using Interpretive Structural Modeling (ISM). Three stages were involved to derive this model: identifying the factors affecting algorithmic trading, validating the elements by empirical research, and then using the modeling and classification of interpretive structures. To gather experts' opinions various interviews were scheduled and the response was taken from 30 experts working in the finance domain. For understanding the relation and linkage between the five variables the ISM model has been used.

Table 1 – Descriptive statistics

Constructs	N	Mini	Maxi	Mean	Std. D
Price volatility	30	1	5	5.23	14.137
Diversification of trades	30	1	5	5.94	16.05
High frequency trading	30	1	5	6.19	16.724
Operational efficiency	30	1	5	5.29	14.316
Back testing ability	30	1	5	6.06	16.383
Human intelligence	30	1	5	5.16	13.957
Algorithmic trading strategies	30	1	5	6.32	17.071
Arbitrage opportunities	30	1	5	4.97	13.43
Volume weighted average price (VWAP)	30	1	5	5.55	14.997
Big data and artificial intelligence	30	1	5	6.00	16.201
Valid N (listwise)	30				

At first ten variables were identified. Variables are shown in Table 1. Expert opinion was taken from those belonging to the finance domain. Descriptive variables were listed from literature review and from this a test of descriptive statistics was conducted and the top five variables having the highest mean were considered for the study. The variables which fulfilled the criteria are listed in table 2 which is given below.

Table – 2 Identified Constructs for ISM analysis.

CONSTRUCTS IDENTIFIED	SUB VARIABLES DEFINING THE CONSTRUCT	CITATIONS
Algorithmic trading strategies	(Momentum investing, Statistical Arbitrage, Performance based)	(Quantinsti,2021), (Frazzini, Israel, & Moskowitz,2014), (Medium,2021), (Syamala & Wadhwa, 2020). (Carrion, 2013)
High frequency trading	(Increase's liquidity, Increase's Efficiency and Speed, Higher Returns for Investors)	(Moneycontrol, 2020), (Investopedia,2021), (Rajalakshmi, 2018). (Lal, 2015), (Menkveld & Jovanovic, 2010). (Cartea & Penalva, 2012).
Back testing ability	(Filtration, Modeling and Optimization, Verification)	(Dell Technologies, 2020), (Philip, Michal & Vidhi, 2013), (Vezeris et al., 2019), (Gunjan, 2019).
Big data and artificial intelligence	(Need for simpler tools, Lowering barriers to entry)	Datacamp, (2020), (NIFM Report, 2017), (Yadav, 2015). (Hilbert & Darmon, 2020), (Joyce, 2020).
Diversification of trades	(Multiple trades at one time, useful in Hedging, can be scanned at executed simultaneously.)	(Capital,2019)

Analysis and results

Interpretive Structural Modeling (ISM) is a technique for summarizing the relation between the factors that define the problem or the issue. Many researchers have been using this technique to understand the relation between the variables. The first step in the ISM technique will be to identify the variables and then show a relation using the structural self interaction matrix (SSIM). Further on we will convert the SSIM matrix into reachaility matrix on the basis of binary digits that is 1 and 0. Moving on a reachability matrix will be created and then the transitivity needs to be verified. After this a final matrix is obtained and then the elements are divided and an summary of the structural model is obtained.

SSIM Structrual self interaction matrix

The SSIM matrix defines the relation among the variables that have been idetified. A group of experts being investors, traders, algorithmic traders, charted accountants, academicians, research scholars were approached for expert opinion. An interview was scheduled with them, and their response was used to identify a relation. In Table 3 there are four symbols V,A,X,O and i, j is used to define the relation. Following are the rules by which the SSIM table was derived.

- The relation from i to j is denoted by V.
- The relation from j to i is denoted by A.
- The relation from i to j and j to i is denoted by X.
- If there is no between i to j and j to i is denoted by O.

Table 3 – Structrual self interaction matrix (SSIM)

J → I ↓	V5	V4	V3	V2	V1
V1	X	X	X	X	-
V2	X	X	A	-	-
V3	V	X	-	-	-
V4	V	-	-	-	-
V5	-	-	-	-	-

Reachability matrix (RM)

To arrive at the Reachability matrix (RM) the SSIM matix was converted into a binary digits (as shown in table 4). The conversion of RM into binary digits was based on rules.Based on SSIM matrix V,A,X,O following were the entries done.

For V (1,0)

For A (0,1)

For X(1,1)

For V (0,0)

Table 4 – Reachability matrix

IJ	V1	V2	V3	V4	V5	Driving variable
V1	1	1	1	1	1	5
V2	1	1	0	1	1	4
V3	1	1	1	1	1	5
V4	1	1	1	1	1	5
V5	1	1	0	0	1	3
Dependent variable	5	5	3	4	5	

Level partioning

From the reachability matrix a Reachability set, and Antecedent set were taken into consideration. To classify the levels, a series of iterations was conducted. Three levels were identified, and they are given in table 5, 6 and 7. In table 5, variable 1 that is algorithmic trading strategies is taken as level 1. In table 6, variable 2 and variable 4 that is high frequency trading and big data and artificial intelligence are taken as level 2. In table 7, variable 3 and variable 5 that is back testing ability and diversification of trades are taken as level 3.

The one way relation is denoted by single arrow, both way relation between the variables is denoted by double arrow and if there is no relation then no arrow is drawn between them (this is represented in the Figure 1).

Table 5 – Level partioning (Level 1)

IJ	Reachability set	Antecedent set	RS ∩ AS	Level
V1	12345	12345	12345	Level 1
V2	1245	12345	1245	
V3	12345	134	134	
V4	12345	1234	1234	
V5	125	12345	125	

Table 6 – Level partioning (Level 2)

IJ	Reachability set	Antecedent set	RS ∩ AS	Level
V2	245	2345	245	Level 2
V3	2345	34	34	
V4	2345	234	234	Level 2
V5	25	2345	25	

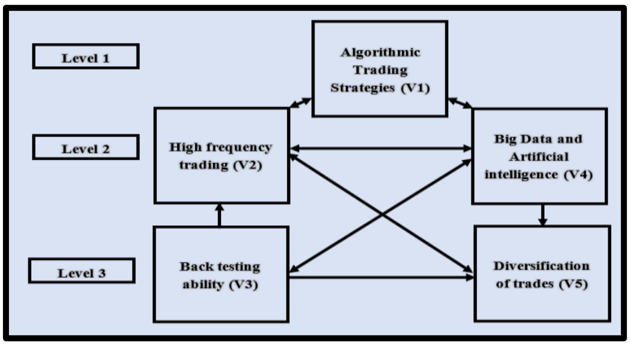
Table 7 – Level partioning (Level 3)

IJ	Reachability matrix	Antecedent Matrix	RS ∩ AS	Level
V3	35	3	3	Level 3
V5	5	35	5	Level 3

Table – 8 – Level Matrix

Level	Variable
1	Algorithmic Trading Strategies
2	High Frequency Trading
2	Big Data and Artificial intelligence
3	Back testing ability
3	Diversification of trades

ISM Model



The figure shows that there is a strong interlink between Algorithmic trading strategies and big data and artificial intelligence. Also, Algorithmic trading strategies and high frequency trading are very important aspects for each other because if we use algorithms for high frequency trading it would increase liquidity and improve efficiency in trading. As Artificial intelligence also plays an important role it also helps us in making back testing strategies and implementing them which will help us to make more profit as our probability increases if we analyse the past data and make future trades. This study was based on identification and modelling of algorithmic trading strategies which will help us in assessing its impact on the Indian stock market and stakeholders. All the variables identified by the researcher turned out to be important as they are related to each other. The model proposed in this paper can be used to assess the impact of algorithmic trading which are effective and practical.

LIMITATIONS AND FURTHER RESEARCH DIRECTIONS

The limitation of ISM model is that the number of respondents was limited to 30 and the response may vary if the sample size is increased. The ISM findings may need some changes if applicable in real world contexts. The conceptual model proposed can be empirically validated by using advanced statistical techniques.

MANAGERIAL IMPLICATIONS

Over the years trading in India has changed a lot from physical trading to online trading and even today new features are being introduced day by day with the help of technology which makes trading even easier. Traders have become technical; they gather information from charts to successfully execute their trade which is purely arithmetic, and algorithms have made their life even easier. Algorithmic trading has bought a whole new era to the Indian stock markets and its benefits are yet to be realized.

The research study can be very useful to assess the impact of algorithmic trading on Indian stock market as broker. Contextual relationship between variables and its influence can be tested practically.

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