International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 4 Apr 2022, pp: 618-627 www.ijaem.net ISSN: 2395-5252

Algorithmic Trading (AT) in Indian Stock Exchange (Stock Market)

Pooja Panjwani, Ankur Jain
Dr. MPS Memorial College of Business Studies, Agra
Assistant Professor, Dr. MPS Memorial College of Business Studies, Agra

Submitted: 05-04-2022 Revised: 14-04-2022 Accepted: 17-04-2022

ABSTRACT
The driving forces behind financing worldwide have been technology and creativity. One such technical advance is algorithmic trade (AT) to minimize risks and maximize returns and comply with developments in the financial market. While AT is widely used globally, academic research on AT testing in most markets is lacking. The absence of evidence is due to uncertainty in and interchangeable use of meanings for AT and high-frequency trading (HFT). Further, the lack of evidence hinders the perception and understanding of the effect on the social machinery of global economies of rising exponential increase in financial transaction velocity. The simple meaning and identity of AT in the Indian stock market are used to demonstrate and view AT as an aspect of financialization transaction speed. We also try to decode the effect of AT on the price discovery mechanism by symbolizing the transaction speed aspect of finance.

Keywords: Algorithmic Trading (AT), High-Frequency Trading (HFT), Indian Stock Market, Financialization, Trading

I. INTRODUCTION

Logarde-Segot (2016) points to the dramatic shift in the equation of society, the economy, and finance due to the unparalleled pace of financial transactions coupled to the growth of the financial field and dynamic and sophisticated financial goods. Financialization is the evolving socio-economic-financial dynamic. Ma and McGroarty (2017) embrace the evolving socio-economic-financial complexities of the social machinery concept and contend that technologies have helped financialise and have changed financially. Automated/High-Frequency Trading/Algorithmic Trading was one of the essential financialization elements which led to enormous transaction speed growth. In this article, we symbolize the speed of the transaction (an aspect of financing in Logarde-Segot (2016)' conceptual framework) with AT.

Johnson (2010) suggests that algorithmic trading (AT) is "a computerized framework focused on rules responsible for performing purchase or selling orders for a particular commodity." It lowers and sometimes avoids a trader's manual interventions and makes effective decisions on time, price, and quantity orders. This decision is dependent on knowledge obtained in the securities and trading centres by dynamically tracking market conditions. The aim is to reduce the demand effect, splitting big orders optimally, and following closely over performance intervals. As an investor or broker, everybody strives to maximize returns and minimize losses by carefully selecting various investment opportunities (Markowitz, 1952). That is also the aim of algorithmic trading. However, in Muniesa (2014), "the stock values are not discovered; they are produced and manufactured." He also believes that the range of algorithmic designed to resolve business challenges leads to new and unpredictable issues. The influence of such technologies in the industry is essential to investigate.

Algorithmic trading uses sophisticated and dynamic statistical methods for making stock market decisions on behalf of a client. Strict guidelines are in place to provide the optimum timing for placing, modification, and cancellation of orders so that it has a minor effect on the price of the inventory and ensures liquidity supply to the investors. Yang and Jiu (2006) note that "the constant pursuit of lower transaction costs and business performance has resulted in increasing demand for advanced trading instruments and algorithmic. Moreover, one such instrument is algorithmic trade."

Algorithmic trading certainly has many benefits over traders. As simulations and decisions based on complex logic in algorithmic trading systems are likely to be faster and more accurate than traders, AT could also lead people traders. When protection is open, the execution of an order dividing orders, selecting various liquidation pools and assimilating information in real-time, etc., is a no more common benefit to AT than typical human traders. The use of AT should then be increased in due course.

In this report, the Securities and Exchange Board of India (SEBI) provides us with a detailed description of AT and its guidance on the explicit recognition of AT. SEBI defines AT as "any order created by automatic logical execution shall be called algorithmic trading." The SEBI regulation to establish the Indian AT audit trail and the AT flag data on the NSE market provides a unique environment to classify AT directly, which otherwise cannot be used on any other markets. In addition to that, SEBI regulation. Therefore, we show proof of algorithmic commerce on the National Stock Exchange (NSE), also part of the emerging markets, taking advantage of its specific location.

II. LITERATURE REVIEW

Aalbers (2017) points out the latest legendary increase in finance and argues that finance opens up unexplored research avenues. He further suggests that "studies are warranted in isolating one aspect from other, in order to allow analytical research first" and "qualitative and disk-based observations, including case studies, are equally relevant." Currie and Logarde-Segot (2016) explain how IT has increased market uncertainty and opaqueness and "requires for analysis to understand the financial systems' fiscal, social, legal and technical changes." Curries and sets (2016) and Gleadle, Haslam, and Yin (2014) and scant literature available on the subject of the AT, its effect on the markets, and financialization elements make this study imperative. The current financialization literature (Logarde-Segost (2010, 2015 and 2015); Ma and McGroarty (2017), Aalbers (2017).

The restricted AT literature is because the data collection with a simple AT identifier is not accessible. Most stock markets do not classify AT, and some proxies have been used (message traffic, order cancellation time, etc.). Results from the use of such proxies have also been recognized as frail or untrustworthy and recommend the use of direct AT measures (Hendershott and Riordan, 2013).

2.1. The Ambiguity in the definition of AT

The meaning of AT has an uncertainty, and AT and HFT are also used synonymously. The Securities and Exchange Commission (SEC) has properly acknowledged this uncertainty in its definition report (2010) and has indicated that HFT is not explicitly specified. SEC recognizes that HFT is an AT subclass. HFT and electronic trading have been applied interchangeably in current literature AT (Chabound et al., 2014, Kelejian and Mukerji, 2016, Hendershott and Riordan, 2013). This mainly occurred because the regulatory authorities lacked a consistent description of AT/HFT. The distinctions between AT and HFT are underlined by Gomber et al. (2011). One of the main distinctions they mention is that HFTs are set off towards the trading day's close.

2.2. The Measurement of AT

Hendershott, Jones, and Menkveld (2011) used the electronic message traffic as proxies for AT volumes. The traffic of messages covers order arrival, cancellation of the order, and exchange reports. Normalized messages traffic: (-1) the number of e-mails per 100 dollars of trading volume is built on the New York Stock Exchange (NYSE) trading algorithmic.

The Automatic Trading Program (ATP) of the German Bursary (Börsenbörse) is based on Hendershot and Riordan (2013). The ATP was an electronic device that decided the price, the amount, and the time the orders were placed. This is one of the first experiments that attempt to classify AT directly. However, the proof of the AT was dependent on the ATP members, who thus included much of the AT, but not all of the AT available during this period.

The AT-study in the foreign exchange market is conducted by Chaboud, Benjamin, Hjalmarsson, and Vega (2004), treating computer-generated trade as AT. They also use HFT and AT synonymously dependent on computer-generated instructions.

Loistl, and Huetl (2007) use AT measurement time as a proxy. They try to distinguish model submissions and order cancellations, which suggest the algorithmic trading operation in turn. They analyze and classify the removal orders depending on the time factor.

2.3. Impact of AT on Markets: Connecting the dots of financialization

The need to connect academic finance to other social sciences and also to integrate financialization principles is emphasized in

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 4 Apr 2022, pp: 618-627 www.ijaem.net ISSN: 2395-5252

Muniesa (2014), Logarde-Segot (2016), McGroarty (2017), Aalbers(2017), Boussart (2016), MacKenzie (2006), and Logarde-Segot and Paranque (2017). Therefore, the effect of recent technical developments on financing obviously must be understood/researched. In order to increase liquidity, one must also be cautious when analyzing the effect of algorithmic configurations (Muneisa, 2014). We are undergoing this analysis in order to understand the effect of the financial (economic) and market participants on the financialization framework transaction rate factor (Logarde-Segot, 2016).

There is little proof of the recent literature on algorithmic trade, and the impacts on market liquidity and uncertainty of AT are varying. Hendershott et al. (2011) say that AT generally increases liquidity, but one of its liquidity measurements is that its analysis "realized expansion" declines causing uncertainty. While they disagree about this choice, they also consider that AT is born in the market and that liquidity suppliers benefit from generating revenue. Aggarwal and Thomas (2014) also discover an excess in order and scope that defies anticipated liquidity patterns. Kelejian and Mukerji (2016) likewise say whether or not AT decreases or increases uncertainty is unknown. Although Groth (2011) shows strongly that algorithmic trade does not raise volatility exceedingly, it at least does not increase more than human traders. Lesmond (2005), Lee (2011), and Lang et al. (2012) say that the uncertainty and liquidity vulnerability in emerging markets are frequently defined. Subrahmanyam (2013) argues that algorithmic trade is sometimes seen as a danger to financial market stability.

Most of the above studies have been conducted with AT and Riordan proxy measurements (2013) which indicate "this proxy makes it difficult to analyze directly how and when ATs act and their function in providing liquidity and demand." This requires future studies in the algorithmic trading field with direct AT detection.

III. EVIDENCE FROM THE INDIAN MARKET

On 22 June 2009, Credit Switzerland Advanced Execution Services (AES) opened Algorithmic Trading (AT) in India. The AT launch is based on the Indian stock. In India in June 2010, the impetus for the AT was gained from the co-location1 allowance by the NSE. Co-location requires servers with brokers to be located side by side to minimize congestion on an exchange server. It was intended to reduce the time needed to transmit data (order) to servers from broker terminals. Since pace is the secret to AT, most courier companies have embraced their server terminals for co-location.

3.1. Data and Sources

NSE DOTEX Order Level used the Historical data from the exchange (NSE) for July 2018 and June 2019. We use these two months split ten months to consider how the AT operation increases/declines over time. The data set includes cash and trading orders. AT (0-Algorithmic, 1 – Non-Algorithmic, 2 –Algorithmic thru SOR, 3 – Non-Algorithmic thru SOR) is included in the data package. Given the simple AT flag, the reliability and authenticity of the proxy and the completeness of the AT-activity data can be excluded. We have combined Algorithmic and Algorithmic Thru SOR (0 and 2) and Non-Algorithmic Thru SOR (1 and 3) respectively in our analysis, as Algorithmic and Non-Algorithmic. The exchange will occur in three ways: Algorithmic trading with Algorithmic and Non- Algorithmic trading with non-algorithmic, and then mixed trade where algorithmic trades with non-algorithmic, or vice versa. Those are classified as Pure Algorithmic, Pure Non-Algorithmic, and Partial Algorithmic. We are using index inventories for CNX Nifty 50 that were reigning for our research at this time.

Two considerations explain the rationale for selecting only Nifty 50 stocks:

1) The CNX Nifty 50 is a well-diversified 50 stock index covering 13 economic sectors.
2) The vast scale of the tick-by-tick data causes difficulties with the analysis technique/technology.

3.2. Evidence and Analysis

By June 2019, 96 percent (7,842 trillion) of the order was invoiced in Nifty 50 (index) shares of algorithmic and 75 percent in number of trades (i.e., 185.84 million). The rise in the proportion of algorithmic orders and businesses in Table 1. (From July 2018 to June 2019). The US industry took nearly ten years to hit a level where AT accounted for 3/4 of transactions, while AT accomplished this feat in India in less than five years. 'Table 1' offers us an overwhelming insight into the AT scope in the Indian economy. This overwhelming scope reflects the openness of business players, policymakers, and other economic and social classes, directly or indirectly affected by the implementation of such technological advances. This can, however, also raise the alarm of caution and observance by the regulatory authorities if harm exists.

Table 1: Nifty 50 Order and Trade Summary

VALUES IN MULTIPLE OF 1,000,000 (X 1 MILLION)	JULY – 18			JUNE – 19		
	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC
ORDER PLACED	4082.37	307.28	93%	7842.37	326.77	96%
NUMBER OF TRADES	112.74	46.49	71%	185.84	60.96	75%
ORDER TO TRADE RATIO	36.21	6.61		42.20	5.36	

At the same time (by June 2019), there were 42.20 and 5.36 order to trade ratio of algorithmic and non-algorithmic (in the 50 stocks of Nifty). Order to trade ratio for algorithmic orders has risen by 16.54 percent, while the order to trade for non-algorithmic has decreased by 18.91 percent (36.21 in July 2018 to 42.20 June 2019) over the same time (6.61 in July 2018 to 5.36 in July 2019). A drop in order to trade ratios for non-algorithmic traders shows that AT stuffs the quotes to generate counterfeit liquidity, then takes advantage of its pace and trading orders, leaving most non-algorithmic orders untraded. The quota strategy and front running strategies will impede a true securities price discovery. This will also worry financial market authorities, who seek to provide effective competition and equal opportunities for all players in the market. The government or economic policy may also be affected because increasing AT supremacy could imply the loss of non-algorithmic/manual traders and replace them over a long period.

"Table 2" below shows the kind of orders AT and non-AT sites. The orders are divided into three categories: (1) the entry orders, which are the first orders placed by the investors in the industry. (2) Cancel order: these are cancelled orders dragging the order out of the market and (3) modified order: these orders are revised and represent changes in price or size, or executive character. The share of algorithmic in each form of order is enormous and rose from July 2018 to June 2019. The proportion of adjusted orders indicates the ability of AT to provide facts or news in pricing during business hours. It can collect information from ever-increasing microblogs, websites for social networks (Twitter, Facebook, etc.), news sites, and many other sources spread around the world and interconnected through the Internet. The rising number of mobile users has strengthened this. However, when you collect the news, you have to be careful, depending on your reputation. Since the sharp change in AT orders (approximately 18 times compared to only 1.8x non-algorithmic traders, in June 2019) may entail the influence or effectiveness of AT networks, this domination must be carefully monitored by other civil, juridical, economic and financial stakeholders to prevent potential Knight Glitches and Flash Crashes.

Table 2: Nifty 50 Orders Detailed Summary

VALUES IN MULTIPLE OF 1,000,000 (X 1	JULY – 2018			JUNE – 2019		
	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC	ALGORITHMIC	NON-ALGORITH	SHARE OF ALGORITHMIC

MILLION)					**MIC**	
ORDER PLACED	4082.37	307.28	93%	7842.37	326.7 7	96%
ORDER CANCEL LED	114.29	28.57	80%	237.10	20.62	92%
ORDER ENTRY	175.05	111.92	61%	356.3	118.7 7	75%
ORDER MODIFIE D	3793.03	166.79	96%	7248.97	187.3 8	97%

Table 3 shows that over 95% of the number of stocks ordered on the market comes from algorithmic orders. The table also shows a decrease in the amount of non-algorithmic ordered. This represents a reduction in the operation of non-algorithmic, and one may argue that AT eliminates industry non-AT competitors and motivates more prominent players on the market to compete with the arms. In addition, this will increase awareness among regulators to protect retail investors. It would also dis-incentivize the central role of stock markets to collect public funds, but driving them away would mean losing sight of markets as a place of investment for institutional investors and raising routes for companies to raise capital. This means that wealth and resources collect in a few hands and impede the general economy and the collapse of systems in corporate governance.

Table3: Nifty 50 Order Volume (Qty. of Share) Summary

VALUES IN MILLIO N OF 1,000,000 (X 1 MILLIO N)	**JULY – 18**			**JUNE – 19**		
	ALGORITH MIC	**NON-ALGORITH MIC**	**SHARE OF ALGORITH MIC**	**ALGORITH MIC**	**NON-ALG ORIT HMIC**	**SHARE OF ALGORI THMIC**
VOLUM E OF ORDERS QTY)	2149179.88	113114.7	95%	5220763.26	10654 6.21	98%
DISCLO SED VOLUM E (QTY)	102098.75	11344.31	90%	955717.32	9653.7 0	99%

Market participants are free to disclose the amounts of stock they wish to purchase or sell while making orders. Market participants can opt to divulge a fraction of the amount ordered (a minimum of 10 percent). They do so to safeguard the stocks from dramatic price increases and minimize the effect costs. In June 2019, the volume reported by AT accounted for more than 99% of the overall volume reported a rise of 41.36% from July 2018. Although the total amount revealed is below, some traders appear to profit from it more than non-algorithmic traders.

Algorithmic orders is also the leading market provider of liquidity, as seen in Table 4. Limit orders are 99.9 percent of algorithmic orders. In July 2018 and June 2019, AT's share of the total liquidity supply is 94% and 96%, respectively. This may mean AT's commitment to the liquidity improvement of the Indian economy. One can argue (Muniesa 2014) whether there is real liquidity given or if there is a short-lived modeled or simulated liquidity. We study the nature of orders by algorithmic in order to validate the same.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 4 Apr 2022, pp: 618-627 www.ijaem.net ISSN: 2395-5252

Table 4: Nifty 50 Order Category (Limit/Market Orders) Summary

VALUES IN MULTIPLE OF 1,000,000 (X 1 MILLION)	JULY – 18			JUNE – 19		
	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC
ORDERS PLACED	4082.37	307.28	93%	7842.37	326.77	96%
MARKET ORDERS	13.41	27.22	33%	18.18	35.29	34%
LIMIT ORDERS	4068.96	280.05	94%	7824.19	291.47	96%

About the immediate or cancel orders, we discuss the essence of orders (Non-IOC). From 'Table 5' we observe the fact that specific instructions are not escaping orders (IOC) so that they can be executed on a basis much longer than anticipated from AT. This is a positive indicator for policymakers and industry players. In July 2018 and June 2019, over 99 percent of orders on the market are non-IOC orders. This is somewhat relaxing for the literature on finance, in which high-frequency trade has always been considered harmful for the social machinery.

Table 5: Nifty 50 Order Category (Immediate or Cancel (IOC) Orders/ Mon-IOC Orders) Summary

VALUES IN MULTIPLE OF 1,000,000 (X 1 MILLION)	JULY – 18			JUNE – 19		
	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC
IOC ORDERS (Y)	12.15	0.25	98%	26.46	0.27	99%
NON-ORDERS (N)	4070.22	307.03	93%	7815.91	326.50	96%

We also look at the unilaterality of the instructions for AT. In the case of algorithmic or non-algorithmic orders, purchasing and selling orders are the same as seen in "Table 6." In July 2018, orders for AT Buy Orders and Sell Orders were 61.83% and 38.17%. In June 2019, AT Buy Orders and Sell Orders were 53.45% and 46.55%, respectively. In July 2018, the composition of the Buy and Sale Orders by non-algorithmic orders showed a similar pattern. A buying order of 59.42% and a selling order of 40.57% are produced from all non-algorithmic trade orders in July 2018. Similarly, the buy and sale orders by non-algorithmic traders in June 2019 was 53.31% and 46.68%.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 4 Apr 2022, pp: 618-627 www.ijaem.net ISSN: 2395-5252

Table 6: Nifty 50 Buy/Sell Orders Summary

VALUES IN MULTIPLE OF 1,000,000 (X 1 MILLION)	JULY – 18			JUNE – 19		
	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC	ALGORITHMIC	NON-ALGORITHMIC	SHARE OF ALGORITHMIC
BUY ORDERS	2423.91	182.44	93%	4177.86	174.07	96%
SELL ORDERS	1646.31	124.58	93%	3638.05	152.42	95%

We have seen the domination of AT orders, but selling the importance of these orders is more important for the market discovery process. We investigate the trading by algorithmic and non-algorithmic and find that AT leads even in the field of trading, and over time the contribution of AT to trades has risen (see "Table 7"). While the number of transactions in both the Algorithmic and Non-Algorithmic categories has risen, non-Algorithmic trades, the amount traded by them has dropped in both categories. That is a temporary respite for regulators and traders from non-Algorithmic. The finding that AT dominates both the purchase and sale can mean one thing: AT mainly trades with AT, or AT's knowledgeable traders make non-algorithmic traders less involved on the market because they are afraid to be picked up from the wrong side of the exchange. We discuss our classifications of trade categories like pure algorithmic, pure non-algorithmic, and partial algorithmic trades with the above claim on whose trade we are dealing with.

Table 7: Nifty 50 Trades and Trends

VALUES IN MULTIPLE OF 1,000,000 (X 1 MILLION)	JULY - 18			JUNE – 19		
	ALGORITHMIC	NON-ALGORITHMIC	CUMULATIVE	ALGORITHMIC	NON-ALGORITHMIC	CUMULATIVE
NUMBER OF TRADES	112.74	46.49	159.23	185.84	60.96	246.80
% NO. OF TRADES	71%	29%	100%	75%	25%	100%
NUMBER OF BUY ALGORITHMIC	78.49	80.74	159.23	134.20	112.54	246.74
% NO. OF BUY ALGORITHMIC	49%	51%	100%	54%	46%	100%
NUMBER OF SELL ALGORITHMIC	73.44	85.79	159.23	131.25	115.49	246.74
% NO. OF SELL ALGORITHMIC	46%	54%	100%	53%	47%	100%

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 4 Apr 2022, pp: 618-627 www.ijaem.net ISSN: 2395-5252

We look at the trade according to our categorization (see Table 8) and note that in just a year, from July 2018 to June 2019, the pure algorithmic almost doubled. This may signify that the war of algorithmic starts or is defined as the arms race in the current literature. Many with more funds to invest in the new technologies and algorithmic will win. Shortly, it must be closely studied how this impacts the current social-finance trends. It should be noted that most trades are currently being generated by partial trade, which means algorithmic. This implies AT dealing in non-AT traders often, which may explain the decrease in the order of non-AT above. Non-AT traders are constantly worried that the AT will take them on board. In the partial algorithmic trades, there is also progress. At the moment, it is relaxed that AT is dealing more often than ever with another AT and that AT is not only targeted towards non-algorithmic traders. However, the partial algorithmic businesses also dominate in absolute terms, so policymakers and other players must be warned of the impacts of AT on consumer efficiency and participants in the market.

Table 8: Who is trading with whom?

VALUES IN MILLION (X 1 MILLION)	JULY - 18		JUNE - 19		Change
	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	PERCENTAGE
PURE ALGORITHMIC TRADES	38.82	24%	77.13	31%	99%
PURE NON-ALGORITHMIC TRADES	46.32	29%	61.88	25%	34%
PARTIAL ALGORITHMIC TRADES	74.09	47%	107.73	44%	45%

From the above findings, we can see that algorithmic trading has been growing in India over the last five years. In the US, the volume business in Algorithmic Trades took over ten years to hit 73 percent (Hendershott et al. 2011), while in India, volume trade by AT has risen to 60 percent in less than five years (64 percent by Rupee/$ Trade Volume, NSE Data). AT accounted for 93.45% of orders placed in India by July 2018 (NSE, Nifty 50 stocks). The data we used registered orders and transactions in the 65536th fraction (jiffies). Our findings explicitly contribute to the transaction velocity aspect in the literature on financing. As the fundamental thinking phase of financialization continues, we must examine further the influences of the growing domination of financial players, economies, practices, and metrics their narratives on different scales.

IV. CONCLUSION, DISCUSSION, AND SCOPE FOR FUTURE RESEARCH

We note that AT orders result in more transactions than orders from non-AT with slower trading speeds. The quantity of orders put by AT is stunning, and AT is also at a large margin compared to its share of trades. This raises concerns "in reality; stock pricing is not discovered, according to Muniesa (2014). AT and HFT are unique places where significant investment is required, and a race for better technologies has been conducted (Hendershott et al., 2011 and Budish et al., 2015). So, investors could take the wrong approach to maximize the gains and distort the market discovery mechanism (Ma and McGroarty, 2017). The discussion on the myth of market discovery and price virtuality continues, and the continuing debate is further justified in our research. Based on the trading speed and the complicated network of information, the argumentation of the financing literature (Logarde-Segot, 2016) and our study of algorithmic order adjustment rates will show that AT quickly incorporates some new information stock prices, which will result in better market price discovery. AT supplies liquidity more by putting limit orders on the market, and thus, AT could also improve the total liquidity of the market. While the abstraction in AT and HFT is still visible and contributes more through the darkening pools not visible to most market participants, the growing use of the volume disclosed by AT is a step towards a transparent system, indicating the intention of reducing impact costs and also reducing sea volatility. Indeed, different researchers worldwide need to assess the effect of AT further. In order to prevent misunderstanding of identity and meanings from different speeches, scientists, clinicians, and regulators also should be involved in defining AT.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 4 Apr 2022, pp: 618-627 www.ijaem.net ISSN: 2395-5252

Due to the concept of AT by the regulators and stock trading bodies, in our analysis, there is a benefit in AT direct recognition to provide the audit trail. In their idea release (2010), the US Securities and Exchange Commission (SEC) pointed out the uncertainty and yet failed to create an AT meaning for the simple recognition of AT. AT literature uses AT proxy metrics which also synonymously processes AT and High-Frequency Trading (HFT). This leads to insufficient research on AT facts, making them insufficient to understand its fiscal, social, and regulatory consequences (Lenglet, 2011). Our report also shows that the number of non-algorithmic orders and trades has decreased, raising concerns relevant to other finance researchers. Is this considered to be a market-overcome machine (Dubey, 2016)? What are the (AT) benefits for other industry players? After introducing AT and transparent manual trade, there have been several incidents of people losing their jobs. It offers scope to explore and investigate the effect of AT on financial and honest business and other sectors of the economy, taking into account the literature on finance. Ma and McGroarty (2017) conclude that "these developments have changed the basic characteristics of important facts of the financing market and culture in general."

REFERENCES

[1]. Lagoarde-Segot, T. (2016). Financialization: towards a new research agenda. International Review of Financial Analysis. https://doi.org/10.1016/j.irfa.2016.03.007

[2]. Ma, T., & McGroarty, F. (2017). Social Machines: how recent technological advances have aided financialisation. Journal of Information Technology, 1-17.

[3]. Johnson, B. (2010). Algorithmic Trading & DMA: An introduction to direct access trading strategies. 4Myeloma Press.

[4]. Markowitz, H. (1952). Portfolio selection*. The Journal of Finance, 7(1), 77-91.

[5]. Muniesa, F. (2014). The provoked economy: Economic reality and the performative turn. Routledge.

[6]. Yang, J., & Jiu, B. (2006). Algorithmic selection: a quantitative approach. Trading, 2006(1), 26-34.

[7]. Aalbers, M. B. (2017). Corporate financialization. The international encyclopedia of geography: People, the earth, environment, and technology. Oxford: Wiley.

[8]. Lagoarde-Segot, T. (Ed.). (2010). After the crisis: rethinking finance. Nova Science Publishers, Incorporated.

[9]. Lagoarde-Segot, T. (2015). Diversifying finance research: From financialization to sustainability. International Review of Finance Analysis, 39, 1–6

[10]. Currie, W. L., & Lagoarde-Segot, T. (2016). Financialization and information technology. Journal of Information Technology.

[11]. Gleadle, P., Haslam, C., & Yin, Y. (2014). Critical perspectives on financialization. Critical Perspectives in Accounting, 1, 1–92

[12]. Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. Journal of Financial and Quantitative Analysis, 48(04), 1001-1024.

[13]. Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the machines: Algorithmic trading in the foreign exchange market. The Journal of Finance, 69(5), 2045-2084. [14] Kelejian, H. H., & Mukerji, P. (2016). Does high frequency algorithmic trading matter for non-AT investors? Research in International Business and Finance, 37, 78-92.

[14]. Gomber, P., Arndt, B., Lutat, M., & Uhle, T. (2011). High-frequency trading. Available at SSRN 1858626.

[15]. Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity?. The Journal of Finance, 66(1), 1-33.

[16]. Prix, J., Loistl, O., & Huetl, M. (2007). Algorithmic trading patterns in Xetra orders. The European Journal of Finance, 13(8), 717-739.

[17]. Aggarwal, N., & Thomas, S. (2014). The causal impact of algorithmic trading on market quality, Working Paper, IGIDR FRG.

[18]. Groth, S. S. (2011, February). Does Algorithmic Trading Increase Volatility? Empirical Evidence from the Fully-Electronic Trading Platform Xetra. In Wirtschaftsinformatik (p. 112).

[19]. Lesmond, D. A. (2005). Liquidity of emerging markets. Journal of Financial Economics, 77(2), 411-452.

[20]. Lee, K. H. (2011). The world price of liquidity risk. Journal of Financial Economics, 99(1), 136-161.

[21]. Lang, M., Lins, K. V., & Maffett, M. (2012). Transparency, liquidity, and valuation: International evidence on when transparency matters most. Journal of Accounting Research, 50(3), 729-774.

[22]. Subrahmanyam, A. (2013). Algorithmic trading, the Flash Crash, and coordinated

circuit breakers. Borsa Istanbul Review, 13(3), 4-9.
[23]. Boussard, V. (2016). Finance at work. London: Routledge.
[24]. MacKenzie, D. (2006). An engine, not a camera: How financial models shape markets. Cambridge (Massachussets): The MIT Press.
[25]. Lagoarde-Segot, T., & Paranque, B. (2017). Sustainability and the reconstruction of academic finance. Research in International Business and Finance, 39 (B), 657-662
[26]. Budish, E., Cramton, P., & Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. The Quarterly Journal of Economics, 130(4), 1547-1621.
[27]. Lenglet, M. (2011). Conflicting codes and codings: How algorithmic trading is reshaping financial regulation. Theory, Culture & Society, 28(6), 44-66.
[28].