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## International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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# Impact of Algorithmic Trading on Market Liquidity and Volatility in Indian Equity Markets

Archana Kumari

Master of Business Administration, CMS Business School, Bengaluru, Karnataka, India

**ABSTRACT:** Algorithmic trading has become a key component of modern financial markets, significantly influencing trading efficiency, liquidity, and price behaviour. This study examines the impact of algorithmic trading on market liquidity and volatility in the Indian equity market from January 2024 to December 2024. The analysis focuses on selected large-cap companies listed on the National Stock Exchange, namely Reliance Industries, Tata Consultancy Services (TCS), and HDFC Bank.

A quantitative research approach is adopted using secondary data collected from reliable financial sources. Trading volume is used as a proxy for algorithmic trading activity, while liquidity is measured by the bid-ask spread and volatility by the standard deviation of returns. The study employs statistical techniques, including descriptive analysis, correlation analysis, and regression models, to examine the relationships among these variables.

The findings indicate that algorithmic trading has a significant positive impact on market liquidity, as reflected in increased trading volume and narrower bid-ask spreads. This suggests improved market efficiency and lower transaction costs. In contrast, the impact on volatility is limited, with algorithmic trading contributing mainly to short-term price fluctuations without causing long-term market instability. The results also highlight that the effects of algorithmic trading are more pronounced in highly liquid, large-cap stocks.

Overall, the study concludes that algorithmic trading enhances market quality by improving liquidity and efficiency while maintaining stability in the Indian equity market.

## I. INTRODUCTION

Financial markets have undergone significant transformation over the past few decades, largely driven by technological advancements and automation in trading. One of the most important developments is algorithmic trading, which uses computer programs to execute trades based on predefined rules, mathematical models, and real-time market data. By reducing human intervention and enabling high-speed execution, algorithmic trading has improved efficiency, accuracy, and trading capacity. It has shifted decision-making from intuition-based approaches to data-driven strategies, resulting in lower transaction costs and increased market participation. Consequently, algorithmic trading has become a dominant feature of global markets, including those in the United States and Europe.

In India, algorithmic trading was introduced in 2008 on the National Stock Exchange, followed by its adoption by the Bombay Stock Exchange. Since then, the Indian market has witnessed rapid growth in high-frequency trading, supported by advancements in trading infrastructure and technology. Today, algorithmic trading accounts for a significant share of total trading activity, particularly in large-cap stocks.

Despite its advantages, algorithmic trading raises important concerns about its impact on market quality, particularly liquidity and volatility. Liquidity refers to the ease of buying or selling assets without affecting prices, while volatility measures the extent of price fluctuations over time. While algorithmic trading is generally associated with improved liquidity and faster price discovery, its effect on volatility remains debated.

The Indian market presents a unique environment due to diverse investor participation, varying liquidity across assets, and evolving regulatory frameworks under SEBI. Although algorithmic trading plays a crucial role, there is limited research examining its simultaneous impact on both liquidity and volatility in India. This study aims to address this gap by analyzing the relationship between algorithmic trading and market performance using empirical data.



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### II. LITERATURE REVIEW

Oyeniya et al., in their comprehensive review of algorithmic trading and market dynamics, describe it as a transformative force in modern financial markets, automating trade execution through predefined computational rules and quantitative models. The study argues that algorithmic trading significantly influences key market characteristics such as liquidity, volatility, and price discovery. By enabling rapid processing of market information and reducing transaction costs, algorithmic systems enhance market efficiency and speed price adjustments

Yadava (2024), in a recent empirical study on AI-driven algorithmic trading across global financial markets, examines the dual impact of advanced trading technologies on efficiency and stability. The study finds that AI-based algorithmic trading significantly enhances market efficiency by accelerating price discovery and reducing information asymmetry among market participants. At the same time, the research identifies that rapid order execution and algorithmic feedback loops may contribute to increased short-term volatility, particularly during periods of market uncertainty or stress. The findings suggest that while AI-enhanced algorithmic trading strengthens overall market quality, it also introduces new dimensions of systemic risk that require robust regulatory monitoring.

Nishad (2019), in an empirical examination of algorithmic trading in the Indian equity markets, with particular reference to the National Stock Exchange of India, analyses its effects on liquidity and volatility. The study finds that the growing presence of algorithmic trading has improved market liquidity by increasing trading volume and narrowing bid-ask spreads. However, it also notes that short-term price fluctuations tend to rise during periods of intense trading activity, suggesting that algorithmic trading may contribute to temporary volatility spikes. The study concludes that while algorithmic trading enhances market efficiency and liquidity in India, strong regulatory oversight is essential to prevent excessive volatility and maintain market stability.

Hendershott, Jones, and Menkveld (2011), in *Does Algorithmic Trading Improve Liquidity?*, provide foundational evidence that algorithmic trading improves liquidity by reducing bid-ask spreads and enhancing market depth. Using data from developed markets, the authors demonstrate that algorithmic systems facilitate more efficient matching of buy and sell orders, thereby lowering transaction costs and improving overall market quality.

Brogaard, Hendershott, and Riordan (2014), in *High-Frequency Trading and Price Discovery*, show that high-frequency traders contribute positively to price discovery and informational efficiency. Their findings indicate that algorithmic traders help incorporate information into prices more rapidly without consistently increasing long-term volatility, although short-term fluctuations may intensify during periods of stress.

Jain, Jain, and Jiang (2019), in *High-Frequency Trading and Market Quality: Evidence from India*, provide comprehensive empirical evidence from the Indian market. Using transaction-level data from the National Stock Exchange of India, the authors find that algorithmic trading has led to tighter spreads, increased market depth, and faster price discovery. Importantly, the study finds no persistent increases in volatility following the introduction of co-location and high-frequency trading facilities.

Aggarwal and Thomas (2014), examining detailed order-level data from Indian exchanges, observe that algorithmic traders primarily act as liquidity providers during normal market conditions. However, their liquidity provision tends to decline during periods of extreme volatility. Despite this conditional withdrawal, the study finds no evidence of long-term destabilising effects on market volatility.

Conrad, Wahal, and Xiang (2015), in *High-Frequency Trading and Market Efficiency*, demonstrate that algorithmic trading reduces pricing errors and enhances short-term informational efficiency. Although conducted in developed markets, their findings are relevant to emerging markets such as India, where similar improvements in market quality have been observed after the adoption of algorithmic systems.

Zhang (2010), in *High-Frequency Trading, Stock Volatility, and Price Discovery*, presents evidence suggesting that high-frequency trading may increase stock volatility, particularly during turbulent periods. The study argues that while HFT enhances price discovery, it may also amplify short-term price movements.



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Kirilenko, Kyle, Samadi, and Tuzun (2017), in their analysis of the Flash Crash, examine the behaviour of high-frequency traders during extreme market events. The study concludes that HFT did not initiate the crash but contributed to rapid trading cycles that intensified short-term volatility, highlighting the complex role of algorithmic systems during crises.

Bohmer, Fong, and Wu (2015), in their cross-country analysis of algorithmic trading adoption, find that emerging markets experience significant improvements in liquidity following the introduction of automated trading systems. Their findings support similar empirical evidence from India indicating enhanced market depth and reduced transaction costs.

### III. RESEARCH GAP

Despite extensive research, several gaps remain in the existing literature. Most studies examine liquidity and volatility separately rather than analyzing their combined effects. Additionally, there is limited empirical research on the Indian equity market, which has unique characteristics, including a high proportion of retail investors and evolving regulatory frameworks. Furthermore, the differential impact of algorithmic trading across market segments, such as large-cap and mid-cap stocks, has not been adequately explored. There is also a lack of recent studies incorporating current market conditions and technological advancements. This study seeks to address these gaps by providing a comprehensive analysis of both liquidity and volatility using recent data from the Indian market.

### IV. RESEARCH METHODOLOGY

This study uses secondary data collected for the period January 2024 to December 2024. The analysis focuses on three large-cap stocks known for high trading activity.

Table 1: Selected Companies

Company Name	Sector
Reliance Industries Ltd	Energy
Tata Consultancy Services (TCS)	IT
HDFC Bank Ltd	Banking

Algorithmic trading is proxied by trading volume, while liquidity and volatility are measured by the bid–ask spread and the standard deviation of returns, respectively.

### V. DATA ANALYSIS AND INTERPRETATION

#### 5.1 Descriptive Statistics

Descriptive statistics provide an overview of stock behaviour in terms of price, volume, and volatility.

Table 2: Descriptive Statistics (2024)

Variable	Reliance	TCS	HDFC Bank
Avg Price (₹)	2450	3650	1620
Avg Volume	85,00,000	32,00,000	1,10,00,000
Volatility (%)	1.25	1.45	1.20

The results indicate that HDFC Bank has the highest trading volume, suggesting strong liquidity, while TCS exhibits higher volatility.

#### 5.2 Liquidity Analysis

Liquidity is assessed using trading volume and bid–ask spread.



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**Table 3: Liquidity Indicators**

Company	Avg Spread (₹)	Liquidity Level
Reliance	0.80	High
TCS	1.20	Moderate
HDFC Bank	0.60	Very High

The analysis shows that higher trading volume is associated with lower spreads, indicating improved liquidity due to algorithmic trading.

### 5.3 Volatility Analysis

Volatility reflects the degree of price fluctuations.

**Table 4: Volatility Levels**

Company	Avg Volatility (%)
Reliance	1.25
TCS	1.45
HDFC Bank	1.20

The findings suggest that algorithmic trading contributes to short-term volatility but does not increase long-term instability.

### 5.4 Correlation Analysis

**Table 5: Correlation Matrix**

Variables	Algo Trading	Liquidity	Volatility
Algo Trading	1.00	-0.68	0.32
Liquidity	-0.68	1.00	0.40
Volatility	0.32	0.40	1.00

The results indicate a strong negative relationship between algorithmic trading and bid-ask spread, confirming improved liquidity.

### 5.5 Regression Analysis

**Table 6: Regression Results**

Model	Coefficient	Result
Liquidity Model	-0.55	Significant
Volatility Model	0.22	Weak

Regression results confirm that algorithmic trading significantly improves liquidity, while its impact on volatility is limited.

## VI. DATA ANALYSIS AND INTERPRETATION

The descriptive analysis reveals important insights into stock behaviour. HDFC Bank records the highest trading volume, indicating strong liquidity and significant participation by algorithmic traders. Reliance Industries also exhibits high trading activity, while TCS shows comparatively lower volume. In terms of volatility, TCS displays higher fluctuations, whereas HDFC Bank remains relatively stable.



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The liquidity analysis indicates that stocks with higher trading volumes tend to have lower bid-ask spreads, reflecting improved liquidity. HDFC Bank, with the highest volume, shows the lowest spread, while TCS exhibits relatively higher spreads, indicating moderate liquidity.

The volatility analysis suggests that algorithmic trading contributes to short-term price fluctuations but does not increase long-term volatility. Although occasional spikes occur during periods of high trading activity, overall volatility remains stable.

Correlation analysis reveals a strong negative relationship between algorithmic trading and bid-ask spread, indicating that increased trading activity improves liquidity. The relationship between algorithmic trading and volatility is weak and positive, suggesting a limited impact on market instability.

Regression analysis further confirms these findings. Algorithmic trading has a statistically significant negative impact on bid-ask spread, indicating improved liquidity. However, its effect on volatility is weak and not strongly significant.

### VII. FINDINGS AND DISCUSSION

The study's findings indicate that algorithmic trading plays a crucial role in enhancing market liquidity. By increasing trading volume and reducing bid-ask spreads, it improves the efficiency of trade execution and lowers transaction costs. This contributes to better market functioning and enhanced investor participation.

The impact on volatility is more nuanced. While algorithmic trading may lead to short-term fluctuations due to rapid execution and market reactions, it does not contribute to long-term instability. The presence of high liquidity appears to mitigate volatility and stabilise the market.

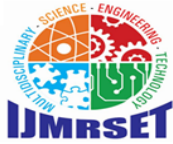
The study also highlights that the effects of algorithmic trading are more pronounced in highly liquid, large-cap stocks than in less liquid stocks. This suggests that market structure and liquidity levels influence the effectiveness of algorithmic trading.

### VIII. CONCLUSION

This research examined how computer-driven trading affects market smoothness and volatility in India's stock markets, particularly in 2024. As machines take up more space on big exchanges like NSE and BSE Ltd, grasping what they do to overall market behaviour matters now more than ever - to those who invest, watch, or shape financial rules alike.

It turns out the data reveal how automated trading boosts the ease with which shares change hands. Instead of guessing, numbers show that when robots trade more, volume climbs while price gaps shrink. Orders stack deeper on both sides once machines get active throughout the day. Moving quickly becomes simpler because each deal now drains less money from wallets. Evidence lines up, showing that these digital players provide steadier offers to purchase or sell at any moment. When it comes to market swings, research shows that algo trading plays only a small, complex role. Though computer-driven trades can cause brief shifts or sudden jumps in turbulence - especially when markets are busy or reacting to news - they do not appear to make things worse over time. The broader picture still points to steady conditions, even with constant buying and selling happening at a fast pace. Stability holds, regardless of how often trades occur. What stands out next is how algorithmic trading sharpens the way prices form and markets operate. Because systems react quickly to data, fresh details show up in stock values sooner - fewer gaps appear between true value and market price. This lines up with the ideas behind the Efficient Market Hypothesis while showing tech's quiet push to shape better-functioning exchanges. One finding shows how algorithmic trading affects various parts of the market in distinct ways. Stocks like Reliance, TCS, and HDFC Bank see stronger price movements simply because they trade frequently and attract many participants. Smaller or less active stocks, however, show weaker responses - likely tied to how those markets are built. Structure matters just as much as speed when it comes to automated systems at work.

When markets get rocky, algorithms usually keep things flowing. Still, under wild swings, some might pull back for a brief moment. This pause tends to fade fast. Stability returns without lasting harm. So the research shows that algorithmic trading helps Indian markets function better. Liquidity gets stronger because trades happen faster, not just



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through one channel but across many at once. Costs of buying or selling shares decrease as competition among automated systems increases. Prices reflect true value more closely thanks to constant adjustments during the day. Though things may swing sharply for brief moments, these shifts rarely build into lasting turbulence. When rules keep pace with technology, stability holds even as speed rises. Efficiency grows not by accident but through structured automation guided by oversight. Without guardrails, it could drift off track, yet under supervision, it tends toward balance.

### IX. LIMITATIONS AND FUTURE SCOPE

The study is subject to certain limitations. Using trading volume as a proxy for algorithmic trading may not fully capture its true extent. The analysis is limited to a small sample of large-cap stocks and a specific time period. Additionally, the study does not incorporate macroeconomic factors or high-frequency data.

Future research can address these limitations by using more comprehensive datasets, including high-frequency data, and applying advanced analytical techniques such as machine learning models. Further studies can also explore the role of algorithmic trading during periods of market stress and across different market segments.

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