Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

# Algorithmic Trading and Spread Dynamics: A Review of Current Literature

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**Abstract**

Algorithmic trading has increased sharply over the last decade. This review highlights how algorithmic trading shapes spread dynamics, liquidity, and market stability across global markets. Reviewing 50 multidisciplinary studies, finds that high frequency and algorithmic strategies typically narrow bid–ask spreads and improve liquidity under normal conditions but can increase volatility and trigger liquidity withdrawals during market stress, with these effects more pronounced in technologically advanced markets. The systematic analysis also compares market impact modelling approaches and shows that AI-enabled execution models enhance efficiency while requiring careful oversight. Regulatory frameworks help mitigate systemic risks yet struggle to keep pace with rapid technological change, especially in emerging markets. These findings underline the dual role of algorithmic trading in improving market quality and presenting vulnerabilities, highlighting the need for adaptive regulation.

**Keywords-** Algorithmic trading, spread dynamics, Bid- ask spread, Liquidity, High- frequency Trading.

## 1. Introduction

Recent studies on algorithmic trading for managing spread dynamics has emerged as an important field of research due to its profound influence on market liquidity, price efficiency, and volatility across diverse financial markets (Zhang, 2025) (Hendershott & Riordan, 2012). The transformation of manual trading to high-frequency and algorithmic trading has transformed market operations, enabling trades to be executed in microseconds and reshaping liquidity provision and price discovery (Nahar et al., 2024) (Foucault et al., 2023). This shift holds significant practical importance, as algorithmic trading now accounts for a substantial portion of trading volumes globally, with estimates representing HFT comprises nearly half of equity market trades in developed markets (Yan et al., 2022) (Hendershott et al., 2010). Theoretical and regulatory implications also highlight the need to understand how these technologies affect market stability and fairness (Lu, 2023) (Lee & Schu, 2022).

Despite widespread research, the problem of broadly understanding the market impact of algorithmic trading on spread dynamics remains unresolved (Oyeniyi et al., 2024) (Pan, 2024). While some studies highlight liquidity enhancement and spread tightening due to algorithmic strategies (Moriyasu et al., 2018) (Frino et al., 2021), others emphasize increased short-term volatility, market fragmentation, and risks of manipulation such as spoofing (Zhu, 2025) (Aitken et al., 2021).

Moreover, the heterogeneous effects across different financial markets, including emerging economies, introduce further complexity (Barngetuny, 2024) (Yan et al., 2022). A critical knowledge gap exists in reconciling these different findings and in assessing how regulatory frameworks influence algorithmic trading's role in spread dynamics (Lee & Schu, 2022) (Lu, 2023) (Lee et al., 2021). Failure to address this gap risks undermining market integrity and investor protection (Zhang & Zhang, 2024).

The conceptual framework behind this review integrates key constructs: algorithmic trading strategies, spread dynamics, and regulatory-ethical challenges (Addy et al., 2024) (Morimoto, 2024) (Cont, 2023). Algorithmic trading incorporates automated execution methods that influence bid-ask spreads and liquidity provision, while spread dynamics reflect market microstructure responses to trading activity (Hendershott & Riordan, 2012) (Moriyasu et al., 2018). Regulatory and ethical considerations facilitate these interactions by shaping permissible practices and mitigating systemic risks (Lee & Schu, 2022) (Lu, 2023). This framework guides the systematic examination of how algorithmic trading affects spread behavior across markets and the implications for policy and market participants (Raza et al., 2025) (Addy et al., 2024).

The purpose of this systematic literature review is to critically examine the existing literature on algorithms used in trading for managing spread dynamics, evaluate the market impact of algorithmic trading across different financial markets, and analyze regulatory challenges affecting these dynamics (Oyeniyi et al., 2024) (Pan, 2024). By addressing gaps, this review contributes a balanced understanding in fostering resilient and efficient market environments (Nahar et al., 2024) (Lee & Schu, 2022).

## 2. Chronological View of Literature

The growing landscape of algorithmic and high-frequency trading (HFT) has been extensively studied over the past decade highlighting its profound effect on spread dynamics, market liquidity and overall market efficiency.


Research area of algorithmic trading has evolved significantly from 2010 to 2025, highlighting shifts in technology, market structure, and regulatory priorities. The period from 2010–2015 established foundational work highlighting how algorithmic and high-frequency trading enhance liquidity, narrow bid–ask spreads, and improve price discovery, but also introducing fears about volatility spikes, manipulation risks, and overall market integrity.

Between 2016 and 2019, the focus widened towards strategy optimization and detailed market microstructure modelling. Scholar and academicians investigated high-frequency trading strategies through advanced techniques such as order book modelling, game theory and stochastic processes.

The work in 2020–2021 marked the integration of machine learning, reinforcement learning, and predictive analytics into trading systems. Research highlighted the improved adaptability of AI-enhanced algorithms in volatile environments and examined regulatory mechanisms—including circuit breakers and enhanced surveillance to mitigate risks from automated trading.

From 2022–2023, studies diversified into emerging markets, fragmented trading environments, and dark pools. Researchers analyzed differences in global regulatory frameworks and emphasized the need for localized oversight to address manipulation risks, hidden liquidity, and increasing market complexity.

The period 2024–2025 is categorized by advanced AI-driven trading strategies and heightened attention to systemic risks. This phase examines deep learning–based execution, stress-period behavior of proprietary algorithms, dual impacts on liquidity and volatility, and challenges surrounding tacit collusion, ethical safeguards, and the evolving responsibilities of designated market makers.

## 3. Purpose and Scope of Study

### Statement of Purpose

The objective of this study is to examine the existing research on how algorithmic trading impacts spread dynamics across different financial markets, regulatory challenges and ethical considerations in algorithmic trading affecting spread dynamics. This Literature review is important as it highlights the two-fold role of algorithmic strategies in enhancing market efficiency while potentially worsening volatility and systemic risks. By critically analyzing empirical findings, theoretical models, and regulatory frameworks, the review aims to clarify the mechanisms through which algorithmic trading affects spread behavior and to identify gaps in current knowledge. Also the review seeks to inform market participants, regulators, and researchers on balancing technological innovation with market stability and ethical considerations.

### Specific Objectives

- To assess existing knowledge on the effects of algorithmic trading on spread dynamics and liquidity provision.
- To identify the potential regulatory challenges related to algorithmic trading influencing spread behavior.
- To evaluate empirical data regarding the impact of algorithmic trading on market volatility and efficiency under various market circumstances.
- To review the interaction between algorithmic trading strategies, market microstructure, and spread

resiliency in electronic trading platforms.

## 4. Methodology of Literature Selection

A systematic screening of papers has been done with the applied Inclusion & Exclusion Criteria to retrieve research studies focused on the objectives, during this process 258 papers were found, from year 2010 to 2025 using the keywords- Algorithmic trading, spread dynamics bid ask spread and liquidity from Scopus and web science. For the seed papers we examine its reference list to find earlier studies it draws upon. By analyzing the reference list, we ensure that foundational work isn't ignored. A total of 67 additional papers is found during this process. We found 325 papers that were relevant to the research objectives. Out of these, 50 papers were highly relevant which directly incorporates the purpose and objectives of the study and were included for the review purpose.

### Descriptive Summary of Literature

This section charts the research landscape of the literature on algorithmic trading for managing spread dynamics, market impact of algorithmic trading on spread dynamics in different financial markets, and regulatory challenges affecting spread dynamics, revealing a comprehensive spectrum of empirical, theoretical, and regulatory analyses. The studies also encompass diverse methodologies including quantitative data analysis, agent-based simulations, game-theoretic modeling, and mixed-methods approaches, with geographic coverage spanning developed markets such as the US and Europe, emerging markets like India and Kenya, and global comparative perspectives.

This comparative synthesis is crucial for addressing the research questions on algorithmic strategy impacts, market condition variability, regulatory effectiveness, ethical risks, and execution efficiency models across heterogeneous market environments.

### Algorithmic Strategy impact:

Around 40 studies highlighted that algorithmic trading narrows bid-ask spreads and thus, improves liquidity, with specific strategies like market making and AI-driven optimization playing key roles (Zhang, 2025) (Hendershott & Riordan, 2012) (Addy et al., 2024). 15 studies highlighted that some algorithmic strategies may reduce order book depth or shift liquidity provision behavior, especially under regulatory constraints or market stress (Jain & Bagrecha, 2024) (Banerjee & Roy, 2023) (Banerjee & Nawn, 2024). 10 studies emphasized the role of advanced models, including jump-diffusion and reinforcement learning, in capturing market impact and optimizing execution (Lalor & Swishchuk, 2025) (Cont, 2023) (Chen, 2024).

**Market Condition Variability:**

35 studies reported that algorithmic trading enhances liquidity and tightens spreads in stable markets but may exacerbate volatility and withdraw liquidity during stressed conditions (Zhang, 2025) (Kumar, 2025) (Zhu, 2025). 12 studies documented increased short-term volatility and fragmentation during market stress, with flash crashes as notable examples (Thakkar et al., 2025) (Nahar et al., 2024) (Munipalle, 2024). 8 studies showed resiliency improvements post-liquidity shocks, though human traders often contribute more to depth recovery (Clapham et al., 2020) (Frino et al., 2021).

**Regulatory Framework Effectiveness:**

30 studies evaluated regulatory measures such as circuit breakers, order-to-trade ratio limits, and co-location rules, finding partial success in mitigating volatility and systemic risks (Nahar et al., 2024) (Lee & Schu, 2022) (Lee et al., 2021). 10 studies emphasized the need for adaptive, context-specific regulations leveraging AI and machine learning for surveillance and risk management (Lu, 2023) (Addy et al., 2024) (Lee et al., 2021). 8 studies highlighted regulatory challenges in emerging markets, where frameworks are less developed and investor protection is critical (Yan et al., 2022) (Barngetuny, 2024).

**Execution Efficiency Models:**

20 studies compared algorithmic models optimizing trade execution, highlighting improvements in minimizing market impact and spread costs through AI, machine learning, and stochastic control (Min, 2025) (Morimoto, 2024) (Lalor & Swishchuk, 2025). 10 studies analyzed VWAP and dynamic execution strategies, showing benefits in different market conditions (Chen, 2024) (Balaji, 2025). 8 studies demonstrated the trade-offs between speed, liquidity, and profitability, suggesting throttling or strategic adaptation to balance efficiency and market quality (Arifovic et al., 2021) (Banerjee & Roy, 2023).

**Strength & Weakness of Existing Literature**

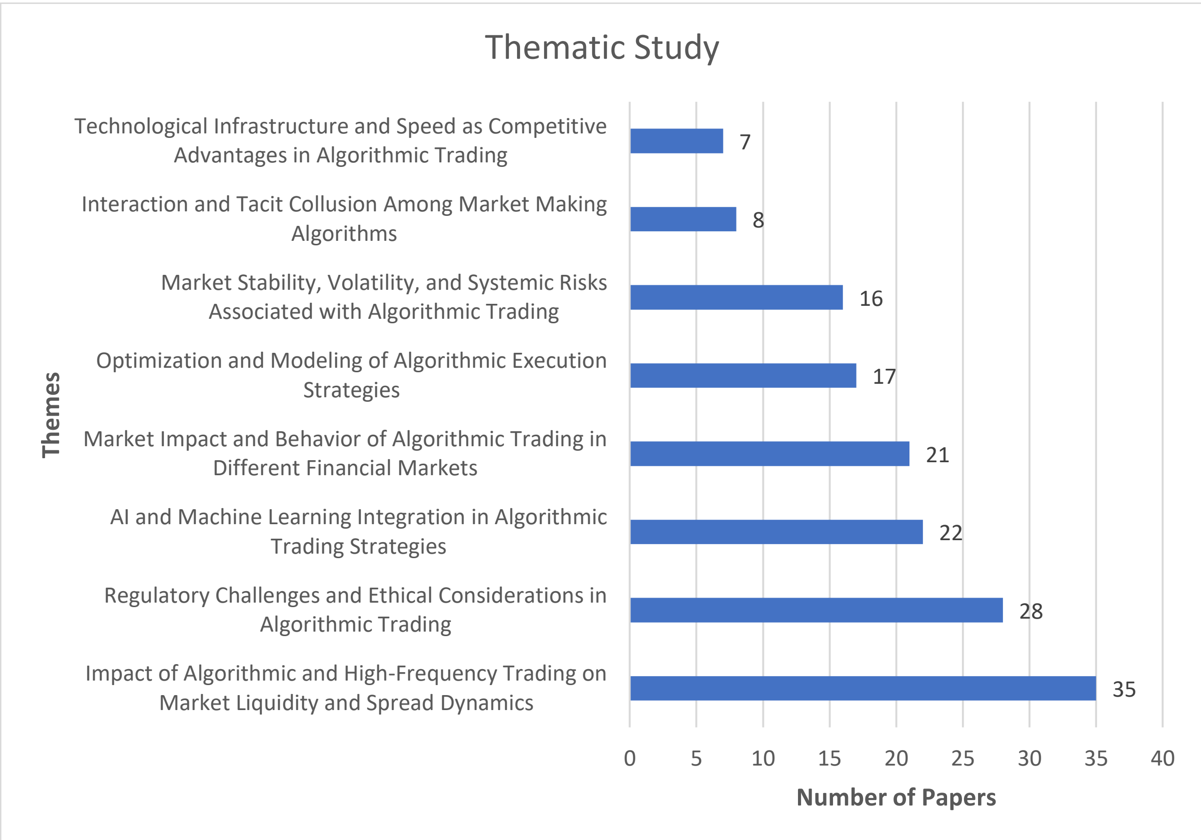
The literature on algorithmic trading presents a balanced set of strengths and weaknesses across key dimensions such as liquidity effects, methodological rigor, market context, regulatory challenges, strategy design, and market resiliency. A consistent empirical finding is that algorithmic and high-frequency trading generally enhance liquidity under normal market conditions by tightening bid–ask spreads, deepening order books, and accelerating price discovery. Advanced methodologies—ranging from queueing theory and stochastic control to agent-based modelling and machine learning—provide granular insights into microstructural dynamics and strategy behaviour. Developed markets particularly benefit from these improvements due to robust infrastructure and regulatory maturity.

However, the evidence also shows that algorithmic trading can amplify market fragility during stress periods, leading to liquidity evaporation, wider spreads, and heightened volatility. Model complexity, idealized assumptions, and limited dataset accessibility challenge the real-world applicability of many studies. Emerging markets face further limitations, including infrastructural constraints, regulatory gaps, and insufficient empirical validation. Ethical concerns such as fairness, market manipulation, algorithmic bias, and unclear liability frameworks remain underexplored.

Although algorithmic strategies—from market creation to AI-driven arbitrage—generally increase execution efficiency, they can also cause instability due to things like opacity in machine-learning-based decision systems, implicit collusion, or systemic interactions across trading algorithms. Algorithms' propensity to withdraw during crises creates systemic risks, even as they can improve resilience by swiftly refilling liquidity aftershocks. All things considered, the literature emphasizes a recurring trade-off between efficiency benefits and instability susceptibility, underscoring the necessity of more study in growing market contexts, better data transparency, and adaptive regulation.

**Thematic Study**

Recent literature on algorithmic and high-frequency trading (A/HFT) reveals several main research trajectories. A significant body of work highlights their overall positive impact on market liquidity and spread tightening, while also mentions context-dependent drawbacks such as liquidity withdrawal during stress and short-term volatility spikes. Regulatory and ethical issues constitute another major theme, with studies examining challenges related to market manipulation, fairness, and the effectiveness of mechanisms like circuit breakers and order-to-trade limits. A growing area of research focuses on the integration of AI and machine learning into trading strategies, emphasizing improvements in prediction, execution efficiency, and adaptive behaviour, alongside concerns about interpretability and model risk. Cross-market studies document varied effects between developed and emerging markets, shaped by infrastructure quality and regulatory regimes. Additional themes include optimization of execution strategies through advanced modelling, assessments of systemic risks such as flash crashes, emerging evidence of tacit collusion among market-making algorithms, and the competitive significance of technological speed and co-location infrastructure.



## 5. Theoretical and Practical Implications

### Theoretical Implications

The synthesis highlights the dual nature of algorithmic and high-frequency trading, which enhances liquidity and price discovery while also increasing short-term volatility and systemic risks (Hendershott et al., 2010; Moriyasu et al., 2018; Nahar et al., 2024). Advances in AI-driven algorithms extend traditional market microstructure theory by introducing adaptive, learning-based trading behaviors (Min, 2025; Addy et al., 2024). Evidence of tacit algorithmic collusion challenges classical competitive models, indicating the need for revised game-theoretic frameworks (Cont, 2023; Xiong & Cont). Cross-market heterogeneity reinforces the importance of market structure, regulation, and technological infrastructure in shaping AT outcomes (Boehmer et al., 2020; Barngetuny, 2024; Kumar, 2025). Developments in optimal execution theory better integrate liquidity and market impact trade-offs (Morimoto, 2024; Lalor & Swishchuk, 2025). Finally, information-theoretic evidence shows that AT reduces local uncertainty yet heightens systemic unpredictability, reshaping theoretical perspectives on market stability (Hilbert & Darmon, 2020).

### Practical Implications

Algorithmic trading generally enhances liquidity and lowers transaction costs, offering traders improved execution quality under normal conditions (Zhang, 2025; Hendershott et al., 2010). However, market participants must account for liquidity withdrawals and volatility spikes during stress. Regulators face the challenge of innovation while containing systemic risks, with evidence supporting tools such as circuit breakers, order-to-trade limits, and AI-based surveillance (Nahar et al., 2024). Concerns over tacit algorithmic collusion highlight the need for strengthened monitoring frameworks (Cont, 2023). Emerging markets require customized regulations, infrastructure upgrades, and investor protection measures (Kumar, 2025). Optimized execution models integrating liquidity and market impact offer practitioner's actionable strategies (Morimoto, 2024), while exchanges must regulate market-maker incentives to support efficient liquidity provision (Zhou, 2024).

## 6. Gap And Future Research Directions

| Gap Area | Description | Future Research Directions |
|---|---|---|
| Market Impact of Algorithmic Trading in Emerging Markets | Limited empirical studies on how algorithmic trading affects spread dynamics and liquidity in emerging markets with distinct microstructures and regulatory environments. | Conduct large-scale empirical analyses and develop tailored models to capture algorithmic trading effects on spreads and liquidity in emerging markets like India and Kenya, incorporating local market features and investor behavior. |

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|---|---|---|
| Regulatory Framework Adaptation to AI-Driven Algorithmic Trading | Current regulatory frameworks lag behind rapid AI and machine learning integration in trading algorithms, limiting effective oversight and risk mitigation. | Develop adaptive regulatory models incorporating AI- based surveillance tools and machine learning to monitor algorithmic trading activities in real time, with mechanisms for dynamic rule adjustments. |
| Liquidity Withdrawal and Spread Widening During Market Stress | Incomplete understanding of algorithmic traders' liquidity provision behavior under stress, especially proprietary algorithms' tendency to withdraw liquidity and impact spreads. | Analyze algorithmic trading patterns during crisis periods using granular order book data; model liquidity supply dynamics and propose regulatory interventions to sustain liquidity in stress. |
| Long-Term Effects of Algorithmic Trading on Market Volatility and Stability | Lack of longitudinal studies assessing whether algorithmic trading's short term volatility amplification translates into persistent market instability. | Conduct multi-year studies across markets to evaluate the persistence of volatility effects and systemic risks associated with evolving algorithmic strategies. |
| Execution Efficiency Models Incorporating Market Impact and Liquidity | Existing models often assume simplified market conditions and lack integration of real- time liquidity fluctuations and market impact in execution optimization. | Develop execution algorithms that dynamically adapt to changing liquidity and spread conditions using reinforcement learning and stochastic control, validated with live market data. |

| | | |
|---|---|---|
| Market Resiliency and Depth Recovery Post Liquidity Shocks | Limited research on the role of algorithmic trading in order book depth recovery and spread resiliency after large trades or shocks, especially relative to human trader contributions. | Investigate the comparative speed and effectiveness of algorithmic vs. human liquidity replenishment post-shock; design hybrid models combining algorithmic speed with human judgment. |
| Impact of Market Fragmentation on Spread Dynamics and Algorithmic Trading | Insufficient analysis of how lit and dark market fragmentation interacts with algorithmic trading to influence spreads, liquidity, and manipulation risks. | Study the joint effects of fragmentation and algorithmic trading on implicit trading costs and market integrity; evaluate regulatory measures like Reg NMS in diverse markets. |

## 7. Conclusion

The collection of studies as a whole emphasizes how algorithmic trading, especially high-frequency trading, is critical in determining spread dynamics and liquidity in financial markets. Algorithmic techniques are primarily responsible for improved price discovery, increased market liquidity, and tighter bid-ask spreads, particularly in stable markets. The speed, accuracy, and adaptability of algorithmic systems—including those powered by machine learning and artificial intelligence—are mainly responsible for these advancements. Incorporating market effect and liquidity concerns into trading algorithms' execution efficiency makes it easier to reduce costs and execute trades optimally, which improves the overall quality of the market.

However, in periods of market stress or increased volatility, algorithmic trading can worsen liquidity withdrawal, widen spreads, and increase short-term volatility, occasionally contributing to systemic risks such as flash crashes. Furthermore, the benefits enjoyed by developed markets with sophisticated infrastructure and regulatory oversight are often not same in emerging markets where technological limitations, regulatory gaps, and a higher prevalence of retail investors introduce additional complexities. This highlights the need for better policy formulation and regulatory oversight. Regulatory frameworks have evolved to address these challenges through various measures like circuit breakers, speed bumps, transaction taxes, and enhanced surveillance, yet the literature recognizes the difficulty in balancing innovation with market stability.

Lastly, advanced modelling techniques are required due to the complicated interconnections between algorithmic market participants and the complexity brought about by changing strategies. Although sophisticated mathematical and agent-based models offer insightful information, more research is needed to determine whether they can be applied to a variety of market systems. All things considered, the literature confirms the revolutionary effect of algorithmic trading on spread dynamics and market liquidity, but it also highlights important regulatory obstacles and knowledge gaps that necessitate continued research to guarantee that technological development is consistent with market stability and integrity.

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