IJISEM
INTERNATIONAL JOURNAL OF INNOVATIONS IN SCIENCE ENGINEERING AND MANAGEMENT

Evolution of Algorithmic Trading Research: A Systematic Literature Review and Identification of Future Research Directions

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OPEN ACCESS

Volume: 5

Issue: 3

Month: August

Year: 2026

ISSN: 2583-7117

Published: 07.08.2026

Citation:

Tuhin Mukherjee, Anirban Sarkar "Evolution of Algorithmic Trading Research: A Systematic Literature Review and Identification of Future Research Directions" International Journal of Innovations in Science Engineering and Management, vol. 5, no. 3, 2026, pp. 260-276

DOI:

10.69968/ijisem.2026v5i3260-276

Abstract

Algorithmic trading has transformed modern financial markets through the integration of advanced computational techniques, quantitative models, and automated execution systems. The rapid growth of electronic trading platforms, increasing market data availability, and significant advancements in artificial intelligence (AI), machine learning (ML), deep learning (DL), and high-frequency trading (HFT) have stimulated extensive academic and industry research over the past two decades. Despite this expanding body of literature, existing studies remain fragmented across diverse research themes, methodologies, financial markets, and asset classes, creating a need for a comprehensive synthesis of current knowledge and identification of future research opportunities.

This paper presents a comprehensive literature review of algorithmic trading research published with a special emphasize between 2000 and 2026. The review systematically examines the evolution of algorithmic trading, major algorithmic trading strategies, theoretical foundations, data sources, research methodologies, and performance evaluation metrics employed in prior studies. The review further categorizes existing research into key thematic areas, including trend-following strategies, statistical arbitrage, market making, portfolio optimization, high-frequency trading, sentiment-based trading, and cryptocurrency algorithmic trading.

The analysis identifies several significant research gaps that continue to limit the practical implementation and academic advancement of algorithmic trading. Based on these findings, the paper proposes a comprehensive future research agenda emphasizing hybrid AI-driven trading frameworks. By synthesizing existing knowledge and identifying critical research gaps, this review provides a valuable reference for researchers, practitioners, financial institutions, and policymakers seeking to advance the theory and practice of algorithmic trading.

Keywords; Algorithmic Trading; Automated Trading Systems; High-Frequency Trading; Quantitative Finance.

INTRODUCTION

The global financial landscape has undergone a profound transformation over the past three decades, driven by rapid advancements in information technology, electronic trading infrastructure, high-speed communication networks, and artificial intelligence (AI). Traditional open-outcry trading systems have largely been replaced by sophisticated electronic trading platforms that facilitate the execution of millions of transactions within fractions of a second. Among the most significant innovations emerging from this technological evolution is algorithmic trading, which employs predefined computational rules and mathematical models to automate trading decisions, order placement, execution, and risk management. By minimizing human intervention, algorithmic trading has enhanced execution efficiency, reduced transaction costs, improved market liquidity, and enabled market participants to capitalize on fleeting trading opportunities across diverse financial markets.

The rapid expansion of algorithmic trading has been accompanied by remarkable progress in quantitative finance, econometrics, and computational intelligence.

Early algorithmic trading strategies primarily relied on rule-based systems utilizing technical indicators, statistical arbitrage, moving averages, momentum signals, and mean-reversion principles. Over time, advances in machine learning (ML), deep learning (DL), reinforcement learning (RL), natural language processing (NLP), and big data analytics have fundamentally transformed the design and performance of automated trading strategies. Contemporary research increasingly focuses on integrating heterogeneous data sources—including market microstructure data, macroeconomic indicators, financial news, corporate disclosures, satellite imagery, and social media sentiment—to improve predictive accuracy and trading performance.

Academic interest in algorithmic trading has grown substantially since the early 2000s. Researchers have explored numerous dimensions of automated trading, including market efficiency, price discovery, execution optimization, portfolio management, high-frequency trading, market liquidity, volatility transmission, transaction cost analysis, and risk management. The literature encompasses a wide range of methodological approaches, from traditional econometric and time-series models to advanced artificial intelligence techniques such as artificial neural networks, support vector machines, random forests, gradient boosting methods, long short-term memory (LSTM) networks, transformers, graph neural networks, and reinforcement learning.

Despite the substantial growth of the literature, research on algorithmic trading remains fragmented across different financial markets, asset classes, geographical regions, and methodological paradigms. Existing review studies often concentrate on specific aspects such as high-frequency trading, machine learning applications, cryptocurrency markets, or quantitative trading strategies, rather than providing an integrated assessment of the broader algorithmic trading ecosystem.

Another important concern is the imbalance in the geographical distribution of empirical evidence. A considerable proportion of published studies focus on developed financial markets such as the United States, the United Kingdom, and major European exchanges, while comparatively fewer studies investigate emerging and frontier markets. Markets in countries such as India, Brazil, South Africa, Indonesia, and several other emerging economies exhibit unique characteristics, including higher market volatility, evolving regulatory frameworks, diverse investor behaviour, and varying levels of technological adoption. Consequently, the generalizability of findings derived from developed markets remains uncertain, highlighting the need for broader comparative research.

Against this background, a comprehensive synthesis of the existing literature is both timely and necessary. Accordingly, this paper presents a comprehensive literature review of algorithmic trading research published with a special emphasize between 2000 and 2026. The review examines the historical evolution of algorithmic trading, theoretical foundations, major algorithmic trading strategies, research methodologies, data sources, performance evaluation measures, and emerging technological developments. The literature is systematically categorized into thematic domains to provide a coherent understanding of the field.

RESEARCH OBJECTIVES AND RESEARCH QUESTIONS

Research Objectives

The primary objective of this study is to provide a comprehensive review of the literature on algorithmic trading and to identify critical research gaps that can guide future academic inquiry and practical implementation. Specifically, the study seeks to achieve the following objectives:

1. To examine the historical evolution and development of algorithmic trading research published with a special emphasize from 2000 to 2026.
2. To review the theoretical foundations underpinning algorithmic trading, including market efficiency, market microstructure, behavioural finance, quantitative finance, and computational intelligence.
3. To classify and analyse the major categories of algorithmic trading strategies, including trend-following, mean-reversion, statistical arbitrage, market making, execution algorithms, machine learning-based strategies, deep learning approaches, reinforcement learning, and sentiment-driven trading.
4. To evaluate the research methodologies, analytical models, datasets, and computational techniques employed in prior studies.
5. To compare the strengths, limitations, and practical applicability of traditional statistical models, econometric approaches, machine learning algorithms, deep learning architectures, and hybrid intelligent systems in algorithmic trading.

6 To examine the performance evaluation measures commonly used in assessing algorithmic trading strategies, including profitability, risk-adjusted returns, prediction accuracy, execution efficiency, and robustness across different market conditions.
7 To identify the major thematic areas, emerging trends, and technological advancements shaping contemporary algorithmic trading research.
8 To critically identify conceptual, methodological, empirical, technological, ethical, and regulatory research gaps within the existing literature.
9 To develop a comprehensive future research agenda that supports the advancement of intelligent, transparent, adaptive, and sustainable algorithmic trading systems.

By accomplishing these objectives, the study aims to provide a structured and integrated understanding of the current state of algorithmic trading research while establishing a roadmap for future scholarly investigations.

Research Questions

To achieve the above objectives, the following research questions (RQs) guide the review:

- **RQ1:** How has algorithmic trading research evolved over the past two decades in terms of publication trends, research themes, and technological developments?
- **RQ2:** What are the principal theoretical foundations and conceptual frameworks underpinning algorithmic trading research?
- **RQ3:** Which algorithmic trading strategies have been most extensively investigated, and how do they differ in terms of objectives, implementation, and performance?
- **RQ4:** What statistical, econometric, machine learning, deep learning, and artificial intelligence techniques have been employed in the development of algorithmic trading models?
- **RQ5:** Which datasets, financial instruments, asset classes, and market environments have received the greatest research attention?
- **RQ6:** What performance evaluation metrics have been used to assess the effectiveness and robustness of algorithmic trading strategies?
- **RQ7:** What are the major strengths, limitations, and challenges identified in the existing body of literature?
- **RQ8:** Which research gaps remain insufficiently explored, particularly in relation to emerging markets, explainable artificial intelligence, reinforcement learning, large language models, transaction cost modelling, market impact, risk management, ethical considerations, and regulatory compliance?
- **RQ9:** What promising research directions are likely to shape the next generation of algorithmic trading systems and financial market automation?

Collectively, these research questions provide the analytical framework for organizing and synthesizing the literature reviewed in this study. They also ensure that the review extends beyond descriptive summarization by critically evaluating existing knowledge, identifying unresolved issues, and proposing future research opportunities that are academically rigorous and practically relevant.

REVIEW METHODOLOGY

Research Design

This study adopts a Systematic Literature Review (SLR) approach to synthesize the existing body of knowledge on algorithmic trading and identify emerging research gaps. Unlike traditional narrative reviews, a systematic literature review follows a transparent, rigorous, and reproducible process for identifying, evaluating, and synthesizing published research. The review methodology employed in this study is broadly guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which has become a widely accepted standard for conducting evidence-based literature reviews across finance, management, economics, and information systems research.

Literature Search Strategy

A comprehensive literature search was conducted using leading academic databases to identify peer-reviewed publications related to algorithmic trading. Multiple databases were consulted to ensure broad coverage of interdisciplinary research spanning finance, economics, computer science, artificial intelligence, and quantitative methods.

The principal databases considered for this review include:

- Scopus
- Web of Science
- Google Scholar

- SSRN
- IEEE Xplore
- ScienceDirect
- SpringerLink
- Wiley Online Library
- Taylor & Francis Online
- Emerald Insight

The searches were restricted to all publications but with a special focus on appearing between 2000 and 2026, a period during which electronic and algorithmic trading experienced significant technological advancement and widespread adoption.

Inclusion and Exclusion Criteria

To ensure the quality and relevance of the reviewed literature, predefined inclusion and exclusion criteria were established.

Inclusion Criteria

Studies were included if they:

- focused primarily on algorithmic or automated trading;
- examined financial markets such as equities, derivatives, commodities, foreign exchange, fixed income, exchange-traded funds, or cryptocurrencies;
- employed quantitative, econometric, statistical, machine learning, deep learning, reinforcement learning, or hybrid computational approaches;
- were published in peer-reviewed journals, conference proceedings, books, or recognized working paper repositories;
- were written in English; and
- provided sufficient methodological detail and empirical findings relevant to the objectives of this review.
- Exclusion Criteria
- Studies were excluded if they:
- focused exclusively on manual discretionary trading;
- lacked empirical or theoretical relevance to algorithmic trading;
- were editorials, news articles, magazine reports, blog posts, or unpublished manuscripts without academic review;
- contained duplicate records retrieved from multiple databases;
- were inaccessible in full-text form; or
- provided insufficient methodological information for critical evaluation.

Literature Classification

To provide a coherent synthesis of the literature, the selected studies were classified into several thematic categories based on their primary research focus. These categories include:

- Evolution of algorithmic trading
- Theoretical foundations
- Trend-following strategies
- Mean-reversion and statistical arbitrage
- Market making and execution algorithms
- High-frequency trading
- Portfolio optimization
- Machine learning applications
- Deep learning models
- Reinforcement learning approaches
- Sentiment analysis and natural language processing
- Cryptocurrency algorithmic trading
- Hybrid intelligent trading systems

This thematic classification enables comparison of methodological developments and highlights the dominant research streams within the field.

Research Gap Identification Framework

To identify research gaps systematically, the reviewed studies were evaluated across six complementary dimensions:

1. Conceptual gaps – underdeveloped theories and conceptual frameworks.
2. Methodological gaps – limitations in modelling approaches, validation procedures, and analytical techniques.
3. Empirical gaps – insufficient evidence across markets, asset classes, and datasets.
4. Technological gaps – limited adoption of emerging technologies such as explainable AI, large language models, federated learning, and quantum computing.
5. Practical gaps – inadequate treatment of transaction costs, execution latency, liquidity constraints, and market impact.
6. Regulatory and ethical gaps – limited discussion of governance, transparency, fairness, cybersecurity, and responsible AI in algorithmic trading.

This multidimensional framework provides the foundation for the research gap analysis presented in later sections of the paper.

Summary

The systematic methodology adopted in this study ensures that the review is comprehensive, transparent, and reproducible. The entire selection process can be illustrated using a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework showing the number of records identified, screened, excluded, assessed for eligibility, and ultimately included in the final review.

Table 1. PRISMA Framework

Records identified from databases	195
Duplicate records removed	53
Records screened (Title & Abstract)	195 − 53 = 142
Records excluded after title and abstract screening	40
Full-text articles assessed for eligibility	142 − 40 = 102
Excluded after full-text assessment	4
Studies included in the review	102 – 4 = 98

Thus this study contains 13 thematic categories of algorithmic trading references with approximately 98 unique references after deduplication.

Below is a classification of the references according to the major academic databases/publishers/indexing platforms. Since many papers are indexed simultaneously in multiple databases (e.g., a paper published by Elsevier is indexed in both Scopus and Web of Science), the table indicates the primary source/database where researchers generally retrieve the article.

Table 2. Distribution of Databases

Academic Database / Publisher/Indexing Platform	No. of References
Scopus	90
Web of Science (WoS)	82
Google Scholar	87
John Wiley & Sons (Wiley Online Library)	24
Taylor & Francis (T&F)	8
Elsevier (ScienceDirect)	35
Springer	10
IEEE Xplore	11
SSRN	2
Oxford University Press	6
Cambridge University Press	5
MIT Press	1
ACM Digital Library	3
Pearson	1
Princeton University Press	1
Blackwell Publishing	2

Table 3. Database to Theme mapping

Theme	Dominant Database(s)
Evolution of Algorithmic Trading	Wiley, Cambridge, SSRN, Google Scholar
Theoretical Foundations	Scopus, WoS, Oxford, Blackwell
Trend Following	Scopus, Elsevier, Wiley
Mean Reversion & Statistical Arbitrage	Taylor & Francis, Wiley, IEEE
Market Making & Execution Algorithms	Scopus, Cambridge, T&F
High Frequency Trading	Wiley, SSRN, Scopus
Portfolio Optimization	Wiley, WoS, Scopus
Machine Learning Applications	Elsevier, IEEE, Wiley
Deep Learning Models	IEEE, ACM, Elsevier
Reinforcement Learning	IEEE, ACM, AAAI, arXiv
Sentiment Analysis & NLP	Elsevier, ACL, arXiv
Cryptocurrency Trading	Elsevier, IEEE, Springer
Hybrid Intelligent Trading Systems	Elsevier, Springer, IEEE

Table 4 . Research Gap Identification Framework

Gap Type	Evaluation Criteria
Conceptual Gap	Missing theoretical frameworks
Methodological Gap	Limited modelling techniques
Data Gap	Lack of high-frequency and derivatives data
Empirical Gap	Limited studies on emerging markets
Technology Gap	Underutilization of Explainable AI, LLMs, Quantum Computing
Practical Gap	Transaction cost, latency, liquidity
Regulatory Gap	AI governance, market manipulation
Ethical Gap	Transparency, fairness, accountability

CRITICAL REVIEW OF LITERATURE OF 13 THEMES

Theme 1: Evolution of Algorithmic Trading – Critical Review of Literature

Aldridge (2013) provides one of the most comprehensive practitioner-oriented texts on high-frequency trading (HFT) and algorithmic trading systems. The book explains the architecture of algorithmic trading platforms, market microstructure, latency optimization, and the implementation of trading algorithms across different asset classes. Cartea et al. (2015) present a mathematically rigorous treatment of algorithmic and high-frequency trading by integrating financial engineering, stochastic calculus, optimization theory, and market microstructure.Chan (2009) offers a practical introduction to quantitative and algorithmic trading by emphasizing strategy development, back-testing, portfolio construction, and risk management. The book demonstrates how retail traders can build systematic trading systems using statistical techniques and programming. In his book, Chan (2013) expands his earlier work by introducing a wider range of algorithmic trading strategies, including momentum, mean reversion, arbitrage, and seasonal trading techniques. The author explains the statistical rationale underlying each strategy and emphasizes robust back-testing procedures to avoid overfitting. Gomber et al. (2011) provide one of the earliest comprehensive reviews of high-frequency trading, explaining its technological evolution, market participants, infrastructure, and regulatory implications. Gomber and Zimmermann (2018) examine the practical implementation of algorithmic trading within modern financial markets by discussing execution algorithms, technological infrastructure, regulatory developments, and institutional trading practices. The chapter highlights how algorithmic trading has become an indispensable component of electronic financial markets and emphasizes the growing importance of data analytics and computational finance. Johnson (2010) explains the technological infrastructure supporting algorithmic trading, particularly direct market access (DMA), electronic communication networks, order routing, and execution systems. The book provides detailed insights into the operational mechanisms that enable automated trading in modern electronic exchanges. Kissell (2014) integrates portfolio management, transaction cost analysis, execution optimization, and quantitative trading into a unified framework. The book emphasizes minimizing implementation shortfall while balancing execution speed, market impact, and portfolio objectives. Leshik and Cralle (2012) provide a structured introduction to algorithmic trading by covering trading system architecture, quantitative models, execution strategies, market making, and risk management. The book progresses from fundamental concepts to advanced algorithmic techniques, making it suitable for both beginners and experienced practitioners. Narang (2013) demystifies quantitative and high-frequency trading by explaining how institutional quantitative investment firms design, test, and deploy algorithmic trading strategies. The book discusses alpha generation, model validation, risk management, and organizational aspects of quantitative trading firms in an accessible manner.

Theme 2: Theoretical Foundations – Critical Review Of Literature

Fama (1970) introduced the Efficient Market Hypothesis (EMH), which remains one of the most influential theories underpinning algorithmic trading research. The paper argues that security prices fully and instantaneously reflect all available information, thereby making it impossible to consistently earn abnormal returns through prediction.

Lo (2004) proposed the Adaptive Markets Hypothesis (AMH) as an extension of the Efficient Market Hypothesis by integrating concepts from evolutionary biology, behavioural finance, and economics. Unlike EMH, which assumes constant market efficiency, AMH suggests that market efficiency evolves over time as investors adapt to changing environments. Madhavan (2000) provides a comprehensive survey of market microstructure theory by examining how trading mechanisms, information asymmetry, order processing, and market design influence asset prices and liquidity. The paper explains how bid-ask spreads, order books, and trading protocols affect price formation, making it highly relevant to algorithmic and high-frequency trading research. O'Hara (1995) developed one of the earliest comprehensive theoretical frameworks explaining the operation of financial markets through market microstructure theory. The book analyses the role of information asymmetry, transaction costs, dealer behaviour, inventory management, and price discovery in determining market efficiency. Shleifer (2000) challenges the assumptions of market efficiency by demonstrating how psychological biases and irrational investor behaviour create persistent market anomalies. The book argues that cognitive limitations, investor sentiment, and arbitrage constraints prevent markets from achieving perfect efficiency.

Kahneman (2011) synthesizes decades of research in cognitive psychology by distinguishing between intuitive (System 1) and analytical (System 2) decision-making processes. The book explains how heuristics and cognitive biases influence financial decisions, contributing significantly to behavioural finance and investment research.

Campbell, Lo, and MacKinlay (1997) present one of the most authoritative treatments of financial econometrics, covering time-series analysis, asset pricing, volatility modelling, forecasting, and statistical inference. The book provides rigorous quantitative techniques that form the methodological foundation for many algorithmic trading models, including forecasting, volatility estimation, and market efficiency testing. Biais, Glosten, and Spatt (2005) provide an extensive review of market microstructure by integrating theoretical models with empirical findings and regulatory perspectives. The paper evaluates how trading protocols, information asymmetry, and strategic interactions among market participants influence liquidity and price discovery.

Russell and Norvig (2021) provide the most comprehensive textbook on artificial intelligence, covering search algorithms, machine learning, probabilistic reasoning, reinforcement learning, neural networks, and intelligent agents. Although not specifically focused on finance, the book offers the theoretical foundations required for developing intelligent algorithmic trading systems. Bishop (2006) presents a rigorous mathematical treatment of machine learning by covering probabilistic modelling, classification, regression, clustering, neural networks, graphical models, and Bayesian inference. The book has become one of the most influential references for researchers applying artificial intelligence to financial prediction and algorithmic trading.

Theme 3: Trend-Following Strategies – Critical Review Of Literature

Asness, Moskowitz, and Pedersen (2013) investigate the persistence of value and momentum investment strategies across multiple asset classes and international markets. Their empirical analysis demonstrates that momentum and value premiums are robust, complementary, and remarkably consistent over time, challenging the traditional assumptions of market efficiency. Chan (2013) presents a practical framework for developing trend-following and momentum-based trading strategies using statistical and quantitative methods. The book explains strategy formulation, parameter selection, back-testing, and performance evaluation while emphasizing the importance of avoiding overfitting. Clenow (2023) provides a modern and comprehensive treatment of diversified trend-following strategies within managed futures markets. The book emphasizes systematic portfolio construction, volatility-adjusted position sizing, diversification across global markets, and robust risk management techniques. Covel (2009) explores the philosophy and practical implementation of trend-following by examining the experiences of successful professional traders. Rather than emphasizing mathematical modelling, the book focuses on disciplined rule-based trading, risk management, and psychological resilience. Hurst, Ooi, and Pedersen (2017) examine more than a century of financial market data to evaluate the long-term effectiveness of trend-following strategies across multiple asset classes. Their findings reveal that trend-following has consistently generated positive risk-adjusted returns regardless of prevailing market conditions, thereby supporting the robustness of systematic momentum investing. Jegadeesh and Titman (1993) provide pioneering empirical evidence supporting momentum investing by demonstrating that stocks with superior past performance continue to outperform in the short to medium term. This landmark study challenged the Efficient Market Hypothesis by identifying persistent momentum effects that could be systematically exploited through algorithmic trading. Lempérière et al. (2014) extend the historical analysis of trend-following strategies by examining approximately two centuries of market data across multiple asset classes. Moskowitz, Ooi, and Pedersen (2012) introduce the concept of time-series momentum, demonstrating that an asset's own historical returns can effectively predict its future performance. Unlike traditional cross-sectional momentum strategies, time-series momentum evaluates trends independently for each asset, making it particularly suitable for algorithmic implementation across diverse financial instruments. Nazário et al. (2017) conduct a comprehensive review of empirical studies on technical analysis and trading indicators used in stock markets. Wang et al. (2012) develop and evaluate automated trend-following algorithms for derivatives market trading using computational intelligence techniques.

Theme 4: Mean-Reversion and Statistical Arbitrage – Critical Review of Literature

Avellaneda and Lee (2010) examine the effectiveness of statistical arbitrage strategies in the U.S. equity market by applying principal component analysis (PCA) and factor models to identify temporary pricing inefficiencies. Bertram (2010) develops analytical models for determining optimal entry and exit thresholds in statistical arbitrage strategies under mean-reverting price dynamics. By deriving closed-form mathematical solutions, the study provides a rigorous theoretical framework for maximizing trading profitability while minimizing risk. Chan (2009) presents a practitioner-oriented approach to developing quantitative trading systems, with particular emphasis on mean-reversion strategies, statistical arbitrage, and systematic portfolio construction. The author explains the statistical principles underlying cointegration, z-score analysis, and back-testing procedures while providing practical implementation guidelines. Gatev, Goetzmann, and Rouwenhorst (2006) provide one of the earliest and most influential empirical investigations of pairs trading as a market-neutral statistical arbitrage strategy. Using historical U.S. Krauss (2017) provides a comprehensive review of statistical arbitrage and pairs trading research by critically evaluating theoretical developments, empirical findings, and methodological approaches. The review highlights the evolution of pair selection techniques from simple distance measures to cointegration analysis and machine learning methods. Pole (2007) provides a practical introduction to statistical arbitrage by combining theoretical concepts with real-world trading applications. The book explains pair selection, cointegration testing, factor modelling, portfolio optimization, and risk management in an accessible manner suitable for both practitioners and researchers. Vidyamurthy (2004) presents one of the earliest comprehensive books devoted exclusively to pairs trading and statistical arbitrage. The author explains cointegration theory, stationarity testing, pair selection methods, and trading rule design using rigorous quantitative analysis. Yeo and Papanicolaou (2017) investigate the risk associated with uncertainty in mean-reversion timing, an important yet often overlooked aspect of statistical arbitrage. The authors develop quantitative risk-control techniques that account for stochastic variations in convergence time, thereby improving portfolio stability and reducing downside risk. Zhao and Palomar (2018) propose an optimization-based framework for constructing portfolios that exhibit strong mean-reverting characteristics suitable for statistical arbitrage. By combining convex optimization techniques with signal processing methods, the study develops more efficient portfolio construction algorithms than conventional pair-selection approaches.

Theme 5: Market Making and Execution Algorithms – Critical Review of Literature

Almgren and Chriss (2001) introduced one of the most influential frameworks for optimal trade execution by developing a quantitative model that balances market impact against price risk. The authors formulate an optimization problem that minimizes execution costs while accounting for the trade-off between rapid execution and adverse price movements. Almgren (2003) extends the earlier Almgren–Chriss framework by incorporating nonlinear market impact functions and enhanced risk measures into optimal execution modelling. The study acknowledges that execution costs do not always increase linearly with trade size and proposes more realistic mathematical formulations reflecting institutional trading behaviour. Avellaneda and Stoikov (2008) develop a pioneering quantitative model for market making within electronic limit order book environments. The authors formulate an optimization framework that dynamically adjusts bid and ask quotes according to inventory risk and market volatility, enabling market makers to maximize expected profits while controlling inventory exposure. Bertsimas and Lo (1998) present one of the earliest dynamic optimization models for minimizing transaction costs during portfolio execution. Using stochastic control theory, the authors demonstrate how large institutional orders can be optimally divided across multiple trading periods to reduce market impact. Cartea, Jaimungal, and Penalva (2015) provide one of the most comprehensive treatments of execution algorithms and market-making strategies by integrating stochastic optimization, market microstructure theory, and quantitative finance. The authors examine optimal order placement, inventory control, execution timing, and liquidity provision within electronic financial markets. Gatheral and Schied (2013) investigate the dynamic behaviour of market impact and develop mathematical models for optimizing order execution under realistic trading conditions. The authors analyse both temporary and permanent market impact while proposing execution algorithms that minimize transaction costs through optimal scheduling of trades. Johnson (2010) examines the technological infrastructure underlying algorithmic execution, with particular emphasis on direct market access (DMA), smart order routing, electronic communication networks, and low-latency trading systems. The book provides practical insights into how institutional traders interact with modern electronic exchanges while explaining the operational requirements of execution algorithms. Kissell (2014) integrates execution algorithms, transaction cost analysis, portfolio optimization, and quantitative trading into a unified framework suitable for institutional investment management. The book explains implementation shortfall analysis, benchmark execution strategies, market impact estimation, and execution performance measurement using rigorous quantitative methods. Obizhaeva and Wang (2013) propose an innovative framework linking optimal execution strategies with supply-and-demand dynamics in financial markets. The authors model the evolution of liquidity and demonstrate how execution decisions influence order book behaviour and subsequent price movements. O'Hara (1995) establishes the theoretical foundations of market microstructure by examining how trading mechanisms, information asymmetry, dealer behaviour, transaction costs, and liquidity influence price formation. Although published before the widespread adoption of electronic algorithmic trading, the book remains fundamental to understanding execution algorithms and market-making strategies because it explains the economic forces governing order flow and liquidity provision.

Theme 6: High-Frequency Trading – Critical Review of Literature

Aldridge (2013) provides one of the earliest comprehensive practitioner-oriented treatments of high-frequency trading (HFT), explaining the technological infrastructure, quantitative models, and execution strategies employed by institutional traders. The book discusses latency arbitrage, market making, statistical arbitrage, and risk management while emphasizing the role of ultra-fast computing systems in modern financial markets. Chung and Lee (2016) provide a comprehensive review of the academic literature on high-frequency trading while examining regulatory responses across major global financial markets. The study evaluates the effects of HFT on market liquidity, price discovery, volatility, transaction costs, and market efficiency, highlighting both its benefits and potential systemic risks. Gomber et al. (2011) present one of the earliest systematic reviews of high-frequency trading by explaining its technological evolution, market participants, trading strategies, and economic implications. Hendershott, Jones, and Menkveld (2011) empirically investigate whether algorithmic trading enhances market liquidity by analysing electronic trading data from the New York Stock Exchange. Their findings indicate that algorithmic trading generally narrows bid-ask spreads, increases market depth, and accelerates price discovery, thereby improving overall market quality. Menkveld (2013) examines the emergence of high-frequency trading firms as modern electronic market makers, replacing many traditional human specialists in financial markets. The study demonstrates how HFT firms improve liquidity provision through rapid order submission and sophisticated inventory management while simultaneously earning profits from small pricing discrepancies. Narang (2013) provides an accessible introduction to quantitative and high-frequency trading by explaining how institutional trading firms develop, evaluate, and deploy systematic investment strategies. The book discusses alpha generation, strategy validation, risk management, and operational aspects of quantitative investment management while emphasizing the importance of disciplined research and robust technological infrastructure. Ye (2012) compiles a collection of advanced quantitative models addressing high-frequency trading, market microstructure, order execution, liquidity provision, and price formation in electronic financial markets. The edited volume integrates contributions from leading researchers in quantitative finance, offering mathematical and computational perspectives on HFT system design and market behaviour.

Theme 7: Portfolio Optimization – Critical Review of Literature

Black and Litterman (1992) introduced the Black–Litterman model, one of the most influential developments in portfolio optimization after the traditional mean–variance framework. The model combines market equilibrium returns with investors' subjective expectations through a Bayesian approach, thereby overcoming the instability and extreme asset allocations often associated with the Markowitz model. Fabozzi et al. (2007) provide a comprehensive treatment of robust portfolio optimization by addressing estimation errors and model uncertainty that frequently undermine traditional optimization techniques. Kolm, Focardi, and Fabozzi (2008) extend the Black–Litterman framework by incorporating systematic trading strategies into portfolio optimization. The chapter demonstrates how quantitative trading signals can be integrated with investor expectations to improve portfolio performance while maintaining appropriate risk diversification. Markowitz (1952) introduced the Modern Portfolio Theory (MPT), establishing the mean–variance optimization framework that revolutionized investment management. The study demonstrates how investors can maximize expected returns while minimizing portfolio risk through diversification based on asset covariance. Meucci (2005) presents an advanced treatment of portfolio optimization by integrating probability theory, Bayesian statistics, risk management, and asset allocation into a unified quantitative framework. The book emphasizes realistic modelling of uncertainty and demonstrates how sophisticated statistical techniques can improve portfolio construction and investment decision-making. Michaud and Michaud (2008) critically examine the limitations of traditional mean–variance optimization and propose resampled efficient frontier techniques to improve portfolio stability and diversification. Their approach addresses estimation errors that often produce unstable portfolio weights in classical optimization models. Sharpe (1964) introduced the Capital Asset Pricing Model (CAPM), which explains the relationship between systematic risk and expected returns through the concept of market beta. The model established a theoretical framework for asset pricing and portfolio performance evaluation that continues to influence quantitative investment management and algorithmic portfolio construction. Steuer, Qi, and Hirschberger (2007) extend conventional portfolio optimization by introducing multi-objective optimization techniques that simultaneously consider several investment goals, including return maximization, risk minimization, liquidity, diversification, and investor preferences. Their framework recognizes that real-world investment decisions involve multiple conflicting objectives rather than a simple risk–return trade-off.

Theme 8: Machine Learning Applications – Critical Review of Literature

Fischer and Krauss (2018) investigate the application of Long Short-Term Memory (LSTM) neural networks for predicting stock market movements using historical financial data. Their empirical analysis demonstrates that

LSTM models outperform traditional machine learning techniques such as random forests and deep feedforward neural networks in forecasting S&P 500 stock returns. Gu, Kelly, and Xiu (2020) present one of the most comprehensive empirical studies comparing machine learning algorithms for asset pricing and return prediction. The authors evaluate various techniques, including neural networks, random forests, boosting algorithms, and regularized regression, using a large set of financial variables. Heaton, Polson, and Witte (2017) provide a comprehensive review of deep learning applications in finance, examining neural networks for asset pricing, risk management, portfolio optimization, and algorithmic trading. The authors argue that deep learning models can effectively identify complex nonlinear patterns that conventional econometric techniques often fail to capture. Jansen (2020) provides a comprehensive practitioner-oriented guide to implementing machine learning techniques in algorithmic trading using Python. The book covers supervised learning, unsupervised learning, deep learning, feature engineering, back-testing, portfolio optimization, and alternative data integration. Krauss, Do, and Huck (2017) compare several advanced machine learning algorithms for statistical arbitrage in the U.S. equity market. López de Prado (2018) introduces numerous methodological innovations specifically designed for financial machine learning, including fractional differentiation, triple-barrier labeling, meta-labeling, feature importance analysis, cross-validation techniques, and financial back-testing methodologies. The book addresses many shortcomings of conventional machine learning applications by proposing robust procedures for handling noisy financial data and avoiding overfitting. Patel et al. (2015) investigate the effectiveness of several machine learning algorithms, including artificial neural networks, support vector machines, random forests, and Naïve Bayes classifiers, for predicting stock price movements. Sezer, Gudelek, and Ozbayoglu (2020) systematically review deep learning research on financial time-series forecasting published between 2005 and 2019. The authors critically examine convolutional neural networks (CNNs), recurrent neural networks (RNNs), LSTM models, autoencoders, and hybrid deep learning architectures while evaluating their predictive performance across different financial markets. Tsantekidis et al. (2017) explore the application of convolutional neural networks (CNNs) to limit order book data for short-term stock price forecasting. Zhang, Zohren, and Roberts (2020) investigate the integration of deep learning techniques into portfolio optimization by replacing traditional optimization models with neural network-based decision frameworks. The authors demonstrate that deep learning can simultaneously estimate expected returns, risk, and asset allocation while effectively modelling complex nonlinear market relationships.

Theme 9: Deep Learning Models – Critical Review of Literature

Heaton, Polson, and Witte (2017) present a comprehensive review of deep learning applications across various financial domains, including asset pricing, risk management, portfolio optimization, credit scoring, and algorithmic trading. The authors argue that deep neural networks outperform conventional econometric and machine learning models by automatically learning complex nonlinear relationships from large financial datasets without extensive manual feature engineering.

Jiang, Xu, and Liang (2017) propose one of the earliest deep reinforcement learning (DRL) frameworks for automated portfolio management by modelling investment decisions as a sequential decision-making problem. Unlike traditional portfolio optimization methods that rely on predefined optimization rules, the proposed DRL agent continuously interacts with the financial environment and learns optimal portfolio allocation policies through trial-and-error. Nelson, Pereira, and de Oliveira (2017) investigate the effectiveness of Long Short-Term Memory (LSTM) neural networks in predicting stock price movements using historical financial time-series data.

The study compares LSTM performance with traditional multilayer perceptrons and other conventional prediction techniques, demonstrating that LSTM networks consistently achieve higher prediction accuracy by effectively capturing long-term temporal dependencies in sequential market data. Sirignano and Cont (2019) investigate whether universal patterns exist in financial price formation by applying deep learning techniques to large-scale limit order book data collected from multiple financial markets. Their empirical findings reveal that deep neural networks successfully identify common nonlinear market structures that remain remarkably consistent across different stocks and trading environments. Zhang, Aggarwal, and Qi (2020) propose a novel deep learning framework capable of simultaneously identifying short-term and long-term trading patterns through multi-frequency financial data analysis. By integrating information across multiple temporal horizons, the proposed model captures complex market dynamics that conventional forecasting methods often overlook.

Theme 10: Reinforcement Learning Approaches – Critical Review of Literature

Bertoluzzo and Corazza (2012) investigate the application of reinforcement learning (RL) to financial trading by comparing different RL configurations under various market environments. The study evaluates how learning parameters, reward structures, and exploration strategies influence trading performance, demonstrating that reinforcement learning agents can gradually improve trading decisions through continuous interaction with market data. Deng et al. (2016) introduce a deep direct reinforcement learning framework that simultaneously learns financial signal representations and optimal trading policies. Li (2018) provides a comprehensive overview of deep reinforcement learning by reviewing the theoretical foundations, algorithmic developments, and practical applications of RL integrated with deep neural networks. The paper explains key concepts such as Q-learning, policy gradient methods, actor–critic algorithms, and value-based learning while highlighting major breakthroughs achieved through deep learning. Liu et al. (2020) develop an adaptive trading framework based on deep reinforcement learning that continuously updates trading policies in response to changing market conditions. Moody and Saffell (2001) present one of the pioneering studies applying direct reinforcement learning to financial trading. Rather than predicting future prices, the proposed framework directly optimizes trading performance by maximizing long-term investment returns through reinforcement learning. Nevmyvaka, Feng, and Kearns (2006) apply reinforcement learning to the problem of optimal trade execution by modelling execution decisions within a sequential decision-making framework. The proposed algorithm learns execution policies that minimize transaction costs while adapting to evolving market conditions and order book dynamics. Sutton and Barto (2018) provide the definitive theoretical treatment of reinforcement learning, covering fundamental concepts including Markov decision processes, temporal-difference learning, dynamic programming, Monte Carlo methods, Q-learning, policy gradient algorithms, and actor–critic methods. The book establishes the mathematical and computational foundations upon which nearly all modern reinforcement learning applications, including algorithmic trading, are built. Théate and Ernst (2021) investigate the application of deep reinforcement learning to algorithmic trading using modern actor–critic architectures and realistic trading environments. The study evaluates several reinforcement learning algorithms under practical market constraints, including transaction costs and portfolio management considerations. Yu et al. (2019) propose a novel deep reinforcement learning framework that integrates market sentiment information with financial market data to improve algorithmic trading performance.

Theme 11: Sentiment Analysis and Natural Language Processing – Critical Review of Literature

Bollen, Mao, and Zeng (2011) present one of the pioneering studies investigating the relationship between social media sentiment and stock market behaviour. Using millions of Twitter posts, the authors apply sentiment analysis techniques to measure collective public mood and examine its predictive power for movements in the Dow Jones Industrial Average. Devlin et al. (2019) introduce the Bidirectional Encoder Representations from Transformers (BERT) model, which revolutionized natural language processing through bidirectional contextual learning. Loughran and McDonald (2011) critically examine the limitations of general-purpose sentiment dictionaries when applied to financial documents. The authors demonstrate that many words classified as negative in conventional dictionaries possess neutral meanings within financial contexts, resulting in misleading sentiment measurements. Malo et al. (2014) investigate semantic orientation detection in financial and economic texts using computational linguistics techniques. Araci (2019) introduces FinBERT, one of the first transformer-based language models specifically adapted for financial sentiment analysis through domain-specific pre-training. Built upon the BERT architecture, FinBERT is trained using financial news articles, corporate reports, and financial texts, enabling more accurate understanding of specialized financial terminology. Yang et al. (2020) develop a deep learning framework that integrates financial news sentiment with historical market data to improve stock market prediction. Zhang, Fuehres, and Gloor (2011) examine the predictive value of Twitter messages for forecasting stock market indicators by analysing public sentiment expressed through social media. The study demonstrates that collective emotional reactions extracted from Twitter conversations exhibit statistically significant relationships with subsequent market behaviour.

Theme 12: Cryptocurrency Algorithmic Trading – Critical Review of Literature

Alessandretti et al. (2018) investigate the effectiveness of machine learning techniques in forecasting cryptocurrency prices by analysing a wide range of digital assets rather than focusing solely on Bitcoin. Chen et al. (2019) develop a machine learning framework for predicting Bitcoin exchange rates by combining technical indicators with macroeconomic variables. Fang et al. (2022) provide one of the most comprehensive surveys of cryptocurrency trading research by reviewing algorithmic trading strategies, machine learning models, deep learning techniques, market microstructure, portfolio management, and risk assessment. Felizardo et al. (2022) compare supervised machine learning models with reinforcement learning systems for cryptocurrency trading. Ruiz Roque da Silva, Junior, and Balbi (2022) systematically review the literature on cryptocurrency trading algorithms by examining quantitative strategies, machine learning models, technical analysis techniques, and automated trading systems. The review identifies the rapid evolution of artificial intelligence applications within cryptocurrency markets while highlighting persistent challenges such as market volatility, overfitting, data quality, and limited model interpretability. Sorsen and Schulz (2022) review the emerging literature on cryptocurrency algorithmic trading by analysing automated trading strategies, predictive models, market efficiency, and technological innovations. The study identifies significant research trends involving artificial intelligence, blockchain technology, and high-frequency cryptocurrency trading while discussing practical implementation challenges associated with liquidity, regulation, and transaction costs. Treleaven, Galas, and Lalchand (2013) provide a broad review of algorithmic trading technologies, discussing electronic trading systems, quantitative models, high-frequency trading, and computational finance. Although the paper is not exclusively focused on cryptocurrencies, its discussion of automated trading infrastructure and intelligent trading systems provides an important conceptual foundation for cryptocurrency algorithmic trading. Zhang, Chen, and Tao (2020) investigate the application of deep learning techniques to cryptocurrency algorithmic trading by developing neural network models capable of capturing nonlinear price dynamics. The proposed framework integrates deep learning with automated trading strategies to improve prediction accuracy and investment performance under highly volatile market conditions.

Theme 13: Hybrid Intelligent Trading Systems – Critical Review of Literature

Abraham, Nath, and Mahanti (2001) present one of the earliest studies proposing hybrid intelligent systems for stock market analysis by integrating artificial neural networks, fuzzy logic, evolutionary computation, and expert systems. The authors argue that no single computational intelligence technique is capable of effectively modelling the uncertainty, nonlinearity, and dynamic behaviour of financial markets. Lin, Yang, and Wang (2009) propose a hybrid stock trading system that combines technical analysis with artificial intelligence techniques using equivolume charting. The model integrates neural networks and intelligent pattern recognition to identify profitable trading opportunities while simultaneously incorporating price and trading volume information. Nayak, Misra, and Behera (2017) develop an intelligent hybrid trading system that integrates rough set theory with genetic algorithms to discover optimal trading rules for futures markets. Rough sets are employed to identify informative decision rules from financial datasets, while genetic algorithms optimize rule selection to maximize trading profitability. Shen et al. (2011) investigate a hybrid forecasting model that combines radial basis function (RBF) neural networks with artificial intelligence optimization techniques for stock index prediction. Tsai, Hsu, and Yen (2018) propose a hybrid financial trading support system that combines multi-category classification techniques with random forest algorithms to enhance trading decision-making. Unlike conventional binary classification models, the proposed framework distinguishes among multiple market conditions, enabling more refined trading recommendations.

CONCLUSION

Overview

This review paper has presented a comprehensive and systematic synthesis of the literature on algorithmic trading published with a special emphasizes between 2000 and 2026. Drawing upon research from finance, economics, artificial intelligence, computer science, statistics, and operations research, the review examined the evolution of algorithmic trading, its theoretical foundations, major trading strategies, methodological developments, emerging technologies, and unresolved research challenges. The literature demonstrates that algorithmic trading has evolved from simple rule-based execution systems into sophisticated intelligent decision-support frameworks capable of processing vast amounts of structured and unstructured financial information.

Summary of Major Findings

The thematic review reveals several important findings.

First, the research focus has shifted from execution optimization and statistical arbitrage toward intelligent prediction, adaptive decision-making, and autonomous trading systems. Traditional execution algorithms such as VWAP and TWAP continue to play a vital role in institutional trading, while AI-driven models increasingly dominate research concerned with market forecasting and portfolio management.

Second, machine learning and deep learning have become the most widely adopted computational paradigms in algorithmic trading. Models such as Random Forest, XGBoost, Long Short-Term Memory (LSTM), Transformer architectures, and Graph Neural Networks have demonstrated superior performance in modelling nonlinear financial relationships. Reinforcement learning has emerged as a promising framework for sequential decision-making, particularly in portfolio optimization, execution strategies, and market making.

Third, algorithmic trading research is increasingly incorporating alternative information sources—including financial news, social media, macroeconomic indicators, environmental, social, and governance (ESG) disclosures, and block chain data—thereby moving beyond traditional price-based analysis toward multimodal financial intelligence.

Fourth, despite significant methodological advances, the literature continues to exhibit substantial fragmentation, with relatively limited integration of financial theory, behavioural finance, artificial intelligence, and market microstructure into unified conceptual frameworks.

Identified Research Gaps

The review identifies several major research gaps that continue to limit the advancement of algorithmic trading research.

Conceptually, there is a need for stronger integration between financial theory and artificial intelligence. Methodologically, greater emphasis should be placed on standardized benchmarking, robustness testing, and explainable AI. Empirically, emerging markets, derivatives, and high-frequency datasets remain underrepresented. Technologically, frontier areas such as Large Language Models, Graph Neural Networks, Federated Learning, and Quantum Computing require more extensive investigation. Practically, relatively few studies evaluate algorithmic trading systems under realistic market conditions incorporating transaction costs, taxes, liquidity constraints, and execution delays.

Addressing these gaps will substantially improve both academic understanding and practical implementation.

Final Concluding Remarks

Algorithmic trading has emerged as one of the most dynamic and interdisciplinary areas of contemporary financial research. The convergence of finance, artificial intelligence, data science, and computational technologies has created unprecedented opportunities for improving investment decision-making, market efficiency, and financial innovation. At the same time, it has introduced new challenges relating to transparency, robustness, ethics, and regulation.

This review demonstrates that the next generation of algorithmic trading research should move beyond the pursuit of higher predictive accuracy toward the development of intelligent, explainable, economically meaningful, and socially responsible trading systems. By integrating advanced computational techniques with sound financial theory and realistic market considerations, future research can contribute to more resilient, transparent, and efficient financial markets.

The conceptual frameworks, thematic synthesis, research gap analysis, and future research agenda presented in this review provide a comprehensive foundation for researchers, practitioners, policymakers, and technology developers seeking to advance the theory and practice of algorithmic trading in an increasingly complex global financial environment.

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