International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

Intraday Trading Across Financial Markets: A Systematic Review of Behavioral, Technical, Quantitative, and AI-Based Trading Strategies

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Abstract:

Intraday trading has emerged as one of the most dynamic areas of financial market research due to advances in electronic trading platforms, algorithmic execution, artificial intelligence, and high-frequency market participation. Despite the rapid expansion of scholarly work, the literature remains fragmented across technical analysis, behavioural finance, market microstructure, quantitative finance, machine learning, and cryptocurrency markets. This study presents a systematic and critical literature review of 81 influential research papers published between 1990 and 2026 to synthesize the evolution of intraday trading research, identify major thematic developments, and highlight unresolved research gaps. The reviewed studies are organized into key themes, including technical trading strategies, candlestick and price action analysis, investor psychology and behavioural biases, market microstructure, momentum and trend-following strategies, volatility spill overs and market connectedness, algorithmic and high-frequency trading, machine learning and reinforcement learning applications, and cryptocurrency and commodity market trading. The review reveals a clear transition from conventional technical analysis toward data-driven and artificial intelligence-based trading approaches, accompanied by increasing emphasis on market efficiency, execution quality, and risk management. However, several limitations persist in the existing literature. Most studies emphasize forecasting accuracy or statistical significance rather than economic profitability after accounting for transaction costs, slippage, liquidity constraints, and execution risks. Furthermore, relatively limited evidence exists on integrated trading frameworks that combine price action, behavioural finance, market microstructure, and artificial intelligence, particularly in emerging markets such as India. By consolidating nearly four decades of research, this review provides a comprehensive knowledge base for researchers, practitioners, and policymakers while proposing future research directions for developing adaptive, robust, and practically implementable intraday trading strategies.

Keywords: Intraday trading; Technical analysis; Price action trading; Algorithmic trading; High-frequency trading.

1. Introduction

Financial markets have undergone a profound transformation over the past three decades, driven by advances in information technology, electronic trading platforms, high-speed communication networks, and the growing availability of real-time market data. These developments have fundamentally altered trading practices, making intraday trading one of the most active and rapidly evolving areas of modern finance. Unlike traditional investment strategies that focus on long-term value creation, intraday trading involves opening and closing positions within the same trading day to capitalize on short-term price movements. The increasing participation of retail investors, institutional traders, proprietary trading firms, and algorithmic trading systems has further intensified the importance of understanding intraday market dynamics.

Intraday trading has attracted considerable attention from both academics and practitioners because of its potential to generate short-term profits and its influence on market efficiency, liquidity, and price discovery. Early studies primarily examined the profitability of technical trading rules, candlestick patterns, moving averages, momentum strategies, and other chart-based techniques. As financial markets became increasingly electronic and competitive, research expanded to include behavioural finance, market microstructure, order flow analysis, volatility spill overs, and quantitative trading models. More recently, advances in artificial intelligence, machine learning, deep learning, reinforcement learning, and high-frequency trading have introduced sophisticated approaches capable of processing vast quantities of financial data and identifying complex market patterns in real time.

The evolution of intraday trading research reflects broader changes in financial markets. Initial investigations focused on testing the weak-form Efficient Market Hypothesis and determining whether technical analysis could consistently generate abnormal returns. Subsequent research demonstrated that investor psychology, including overconfidence, loss aversion, disposition effects, and herd behaviour, significantly influences trading decisions and market outcomes. Parallel developments in market microstructure revealed the importance of order flow, liquidity, bid–ask spreads, and information asymmetry in explaining short-term price movements. More recently, algorithmic trading and artificial intelligence have shifted the research focus toward adaptive trading systems capable of responding to rapidly changing market conditions.

Despite the substantial growth of the literature, existing research remains fragmented across multiple disciplines and financial markets. Studies differ considerably in their theoretical foundations, methodologies, asset classes, sample periods, data frequency, and performance evaluation criteria. While numerous investigations report statistically significant forecasting accuracy or profitable trading signals, comparatively fewer assess the economic viability of trading strategies after accounting for transaction costs, slippage, liquidity constraints, execution delays, and risk-adjusted performance. Furthermore, many studies focus on developed markets, whereas empirical evidence from emerging economies, particularly India, remains relatively limited despite the rapid expansion of electronic trading and retail participation.

Another important limitation is the lack of integration among the major research streams. Technical analysis, behavioural finance, market microstructure, machine learning, and algorithmic trading have often evolved independently, with relatively few studies combining these perspectives into unified trading frameworks. Similarly, the rapid emergence of cryptocurrency markets, high-frequency trading, reinforcement learning, and explainable artificial intelligence has created new opportunities and challenges that have not yet been comprehensively synthesized within the intraday trading literature.

Given these developments, a comprehensive and critical synthesis of the existing literature is both timely and necessary. Such a review can consolidate current knowledge, identify methodological trends, evaluate the strengths and limitations of prior studies, and provide a roadmap for future research. By integrating evidence across traditional financial markets, commodity futures, foreign exchange, and cryptocurrency markets, this review offers a holistic perspective on the evolution of intraday trading research over the past four decades.

Accordingly, this study systematically reviews 81 influential research papers published between 1990 and 2026. The selected studies encompass a broad range of themes, including technical analysis, candlestick and price action trading, behavioural finance, market microstructure, momentum and trend-following strategies, volatility spill overs, connectedness analysis, algorithmic and high-frequency trading, machine learning, reinforcement learning, and cryptocurrency trading. Through a chronological and thematic critical review, the study identifies major research developments, methodological advances, persistent limitations, and emerging research opportunities.

This review makes several important contributions to the existing literature. First, it provides a comprehensive synthesis of nearly four decades of intraday trading research, covering multiple asset classes and methodological approaches within a single framework. Second, it critically evaluates the evolution of trading strategies from traditional technical analysis to artificial intelligence-driven decision-making systems. Third, it identifies persistent research gaps related to economic profitability, real-world implementation, behavioural integration, and emerging market evidence. Finally, it proposes a future research agenda that may assist researchers, practitioners, policymakers, and financial institutions in developing more robust, adaptive, and practically implementable intraday trading strategies.

2. Research Objectives

The rapid evolution of intraday trading over the past four decades has generated an extensive and multidisciplinary body of literature encompassing technical analysis, behavioural finance, market microstructure, quantitative finance, algorithmic trading, artificial intelligence, and cryptocurrency markets. Although these studies have significantly advanced the understanding of short-term trading behaviour and market dynamics, the literature remains fragmented across different theoretical perspectives, methodologies, and asset classes. Consequently, there is a need for a comprehensive synthesis that critically evaluates existing knowledge and identifies promising avenues for future research.

Accordingly, the present study is guided by the following research objectives:

1. To systematically review the evolution of intraday trading research published between 1990 and 2026.
2. To classify the existing literature into major thematic areas, including technical analysis, candlestick and price action trading, behavioural finance, market microstructure, momentum and trend-following strategies, volatility spill overs, algorithmic trading, high-frequency trading, machine learning, reinforcement learning, commodity trading, foreign exchange trading, and cryptocurrency markets.
3. To critically evaluate the principal findings, methodological approaches, and limitations of previous studies in order to assess the current state of knowledge in intraday trading research.
4. To identify the dominant theoretical frameworks and analytical techniques employed in intraday trading studies, including econometric models, statistical methods, technical indicators, machine learning algorithms, deep learning models, and artificial intelligence-based trading systems.
5. To examine the evolution of intraday trading strategies from traditional technical analysis to modern algorithmic and AI-driven approaches and evaluate their reported effectiveness across different financial markets.
6. To identify the major research gaps and unresolved issues in the existing literature, particularly with respect to transaction costs, execution risk, market microstructure, behavioural factors, explainable artificial intelligence, and evidence from emerging markets.
7. To develop a comprehensive future research agenda that supports the design of more robust, adaptive, and practically implementable intraday trading strategies for researchers, practitioners, and policymakers.

The achievement of these objectives enables the study to provide a comprehensive understanding of the intellectual development of intraday trading research over the past four decades. By synthesizing evidence across multiple financial markets and methodological approaches, the review not only consolidates existing knowledge but also highlights emerging research opportunities that may shape the next generation of intraday trading models and decision-support systems.

3. Research Methodology

3.1 Research Design

This study adopts a systematic literature review (SLR) methodology to critically examine the evolution of intraday trading research. Unlike traditional narrative reviews, a systematic literature review follows a transparent, structured, and reproducible process for identifying, selecting, evaluating, and synthesizing relevant studies. The SLR approach minimizes selection bias, enhances methodological rigor, and provides a comprehensive understanding of the existing body of knowledge. Accordingly, this review follows the general principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure a systematic and transparent study selection process.

3.2 Data Sources

Relevant studies were identified through comprehensive searches of leading academic databases, including:

- Scopus
- Web of Science
- ScienceDirect
- SpringerLink

- Wiley Online Library
- Taylor & Francis Online
- Emerald Insight
- JSTOR
- IEEE Xplore
- Google Scholar

These databases were selected because they provide extensive coverage of peer-reviewed journals in finance, economics, management, computer science, artificial intelligence, and financial engineering.

3.3 Search Strategy

The literature search was conducted using combinations of keywords related to intraday trading and its associated research domains. The primary five theme search terms included:

- Price Action Trading and Candlestick Pattern Analysis
- Behavioural Finance and Investor Psychology in Intraday Trading
- Volatility Spill overs, Connectedness, and Systemic Risk
- Machine Learning, Deep Learning, and Reinforcement Learning in Intraday Trading
- Intraday Trading Across Commodity, Foreign Exchange, and Cryptocurrency Markets

Boolean operators (AND, OR) and database-specific filters were used to improve search precision and maximize the retrieval of relevant studies.

3.4 Inclusion and Exclusion Criteria

To ensure the quality and relevance of the review, explicit inclusion and exclusion criteria were established.

Inclusion Criteria

Studies were included if they:

- were published between 1990 and 2026;
- were published in peer-reviewed journals or reputed conference proceedings;
- focused on intraday trading or closely related topics such as technical analysis, algorithmic trading, behavioural finance, market microstructure, or AI-based trading;
- presented empirical, theoretical, methodological, or review-based contributions relevant to intraday trading; and
- were published in the English language.

Exclusion Criteria

Studies were excluded if they:

- focused exclusively on long-term investment strategies without relevance to intraday trading;
- consisted of editorials, book reviews, dissertations, magazine articles, or non-peer-reviewed publications;
- lacked sufficient methodological detail or empirical evidence; or
- were duplicate publications retrieved from multiple databases.

3.5 Study Selection Process

The study selection process followed multiple screening stages. Initially, literature searches identified 200 potentially relevant publications across the selected databases. After removing 62 duplicate records, 138 unique studies remained for title and abstract screening. Subsequently, 20 studies were excluded because they did not meet the review objectives. The remaining 118 articles underwent full-text assessment, during which 37 studies were excluded due to insufficient relevance, methodological limitations, or failure to satisfy the inclusion criteria. Consequently, 81 studies were selected for detailed qualitative analysis and critical review.

The study selection process is summarized using the PRISMA framework as above.

4. Critical Review of Literature

4.1 Price Action Trading and Candlestick Pattern Analysis

Price action trading and candlestick pattern analysis constitute one of the oldest and most extensively studied domains within intraday trading research. Unlike indicator-based approaches that derive signals from transformed price series, price action trading relies directly on historical price movements, market structure, support and resistance levels, and candlestick formations to identify trading opportunities. The underlying premise is that price incorporates all available information and that recurring price patterns reflect the collective psychology of market participants. Consequently, researchers have devoted considerable attention to evaluating whether candlestick patterns and price action techniques possess predictive power that can consistently generate abnormal returns.

One of the earliest empirical investigations into price pattern predictability was conducted by Caginalp and Laurent (1998), who demonstrated that certain price formations exhibit statistically significant forecasting ability. Their findings challenged the strict interpretation of the Efficient Market Hypothesis by suggesting that historical price movements may contain exploitable information. However, the predictive strength of these patterns varied across market conditions, indicating that price action signals are not universally reliable.

Subsequent research shifted toward evaluating Japanese candlestick techniques, one of the most widely practiced forms of price action analysis. Fock, Klein, and Zwergel (2005) examined the profitability of candlestick formations using intraday futures data and reported that several candlestick patterns generated profitable trading signals under specific market conditions. Nevertheless, the profitability was highly dependent on market volatility and rapidly diminished after accounting for transaction costs, indicating that successful implementation requires careful consideration of execution efficiency.

Marshall, Young, and Rose (2006) provided one of the most comprehensive empirical evaluations of candlestick trading strategies across international equity markets. Their findings suggested that although certain candlestick formations occasionally produced statistically significant returns, the overall economic profitability was weak after incorporating realistic trading costs. The study therefore questioned the practical value of relying exclusively on candlestick analysis for investment decision-making.

Research in emerging markets produced mixed evidence regarding the effectiveness of candlestick techniques. Goo, Chen, and Chang (2007) investigated Japanese candlestick strategies in the Taiwanese stock market and found that selected patterns generated profitable trading opportunities during specific market phases. However, the predictive performance varied considerably across different candlestick formations, suggesting that market context plays a crucial role in determining the reliability of price action signals.

Horton (2009) further examined whether candlestick formations could improve stock selection decisions. The study concluded that most traditional candlestick patterns possessed limited incremental predictive ability after controlling for broader market factors. These findings implied that candlestick analysis should be viewed as a complementary decision-support tool rather than a standalone trading system.

The growing availability of high-frequency market data enabled researchers to examine candlestick performance under more realistic trading environments. Lu (2014) evaluated the profitability of candlestick charting in the Taiwan Stock Exchange and reported that while selected patterns exhibited statistically significant predictive ability, much of the apparent profitability disappeared after incorporating transaction costs. The study highlighted the importance of distinguishing between statistical significance and economic significance when evaluating trading strategies.

Recent studies have focused on enhancing traditional candlestick analysis using adaptive and computational approaches. Chong, Ng, and Liew (2014) reassessed the performance of MACD and RSI oscillator-based strategies and argued that combining price patterns with momentum indicators improved forecasting performance compared with isolated technical indicators. This finding suggested that hybrid trading systems integrating multiple technical signals may offer greater robustness than conventional rule-based approaches.

Advances in computational intelligence have further transformed candlestick research. Orquín-Serrano (2020) proposed adaptive candlestick patterns for the EUR/USD foreign exchange market, allowing pattern recognition rules to adjust dynamically to changing volatility regimes. The adaptive methodology demonstrated superior predictive performance relative to traditional fixed-pattern approaches, indicating that flexible trading rules better accommodate evolving market conditions.

The most recent development in this research stream is represented by Moser and Brauneis (2026), who investigated intraday cryptocurrency price forecasting using candlestick patterns. Their study demonstrated that adaptive candlestick recognition models combined with modern statistical learning techniques significantly improved short-term forecasting accuracy in cryptocurrency markets. Nevertheless, the authors acknowledged that predictive improvements did not automatically translate into higher net trading profits once transaction costs, bid–ask spreads, slippage, and execution delays were incorporated.

4.2 Behavioural Finance and Investor Psychology in Intraday Trading

Behavioural finance has become one of the most influential theoretical frameworks for understanding intraday trading behaviour because it challenges the traditional assumption that investors are fully rational and markets are perfectly efficient. While classical finance theories, particularly the Efficient Market Hypothesis (EMH), assume that prices instantaneously incorporate all available information, behavioural finance argues that psychological biases and emotional responses systematically influence investment decisions, resulting in temporary market inefficiencies that may be exploited by intraday traders. Consequently, an expanding body of literature has investigated how cognitive biases, emotions, and behavioural heuristics affect short-term trading performance.

The early foundations of behavioural finance in trading were established by Kahneman and Riepe (1998), who demonstrated that investment decisions are frequently influenced by psychological factors rather than objective analysis. Their work highlighted the roles of overconfidence, loss aversion, anchoring, hindsight bias, and confirmation bias in shaping investor behaviour. These biases are particularly relevant in intraday trading, where decisions must be made rapidly under conditions of uncertainty, high information flow, and considerable time pressure. Their contribution shifted the focus of financial research from purely quantitative models to the incorporation of human decision-making processes into trading analysis.

One of the most influential behavioural phenomena affecting intraday trading is the disposition effect, whereby investors tend to realize gains prematurely while retaining losing positions in the hope of future recovery. Odean (1998) provided compelling empirical evidence supporting this behaviour using brokerage account data, demonstrating that investors systematically sold winning stocks more readily than losing stocks despite the absence of economic justification. This behavioural bias reduces portfolio performance and has important implications for intraday traders, who frequently encounter rapid fluctuations in unrealized profits and losses.

Barber and Odean (2000) further demonstrated that excessive trading significantly reduces investment performance. Their study showed that individual investors who traded most actively earned substantially lower net returns than less active investors, primarily because frequent trading increased transaction costs and reflected excessive confidence in personal forecasting ability. Although the study examined retail investors broadly rather than intraday traders specifically, its findings remain highly relevant because intraday trading inherently involves high trading frequency and repeated decision-making.

Expanding upon this work, Barber and Odean (2001) examined gender differences in investment behaviour and found that male investors generally traded more aggressively than female investors due to greater overconfidence. The higher trading frequency resulted in lower net returns after accounting for transaction costs. Their findings provided strong empirical support for the hypothesis that psychological traits directly influence trading intensity and financial performance.

Behavioural explanations of trading performance were further strengthened by Fenton-O'Creevy, Nicholson, Soane, and Willman (2003), who investigated professional traders rather than retail investors. Contrary to the common assumption that professional experience eliminates behavioural biases, the authors found that traders exhibiting unrealistic perceptions of control performed significantly worse than those demonstrating greater emotional discipline. The study highlighted that psychological biases persist even among experienced market participants and emphasized the importance of emotional regulation in successful trading.

Research in emerging markets has generally confirmed these behavioural patterns. Chen, Kim, Nofsinger, and Rui (2007) examined Chinese investors and reported that overconfidence, representativeness bias, and the disposition effect significantly influenced trading performance. Interestingly, they found that trading experience reduced—but did not eliminate—the impact of behavioural biases, suggesting that learning improves decision quality without fully overcoming cognitive limitations.

Ho (2013) extended behavioural finance into the context of intraday trading by examining overconfidence and private information in the Taiwan Stock Exchange. The study demonstrated that overconfident traders tended to trade more frequently and interpreted private information too optimistically, leading to increased trading activity but not necessarily superior returns. These findings reinforce the view that excessive confidence may increase market participation while simultaneously reducing investment performance.

Behavioural research has also become increasingly relevant within the Indian financial market. Prosad, Kapoor, Sengupta, and Roychoudhary (2018) documented significant evidence of overconfidence and the disposition effect among Indian equity investors. Their findings indicate that psychological biases remain pervasive in emerging markets despite increasing market sophistication and regulatory improvements. The study suggests that behavioural factors should be incorporated into models of intraday trading behaviour in developing economies.

Experimental research has provided additional insights into investor psychology. Trejos, van Deemen, Rodríguez, and Gómez (2019) developed a simulated trading environment to investigate overconfidence and the disposition effect under controlled conditions. Their results confirmed that these behavioural biases persisted even when participants possessed identical information, indicating that irrational decision-making originates primarily from cognitive processes rather than informational disadvantages.

Recent research has expanded the behavioural literature beyond traditional cognitive biases by incorporating behavioural reference points and heuristic decision-making. For example, Laubsch, Smales, and Vo (2024) demonstrated that traders' behaviour in commodity futures markets is significantly influenced by 52-week high and low price levels. These reference prices serve as psychological anchors that affect trading decisions even when they possess limited fundamental significance, illustrating the continuing importance of behavioural heuristics in financial markets.

4.3 Volatility Spill overs, Connectedness, and Systemic Risk

The increasing integration of global financial markets has substantially transformed the nature of intraday trading by accelerating the transmission of information across asset classes, sectors, and geographical regions. Consequently, understanding volatility spill overs and market connectedness has become an essential component of intraday trading research, as traders increasingly recognize that price movements in one market may rapidly influence the behaviour of other markets. The growing availability of high-frequency financial data has further enabled researchers to examine these dynamic interactions with greater precision, leading to significant advances in the measurement of systemic risk and information transmission.

The modern literature on financial connectedness was pioneered by Diebold and Yilmaz (2009), who introduced a spill over index based on forecast error variance decomposition (FEVD) within a vector autoregressive (VAR) framework. Their methodology provided a comprehensive measure of return and volatility spill overs among financial markets, allowing researchers to quantify both the magnitude and direction of information transmission. The study demonstrated that volatility shocks are not confined to individual markets but propagate across financial systems, particularly during periods of economic and financial instability. This framework represented a major methodological advancement by shifting attention from isolated market analysis to interconnected financial networks.

Building upon this foundation, Diebold and Yilmaz (2012) proposed directional volatility spill over measures that distinguished between volatility transmitted to other markets and volatility received from them. This refinement enabled researchers to identify net transmitters and net receivers of market risk, thereby improving the understanding of financial contagion and systemic vulnerability. The directional connectedness framework has since become one of the most widely adopted methodologies in financial economics, particularly for examining intraday information transmission and portfolio risk management.

Subsequent research recognized that volatility spill overs are frequently asymmetric. Baruník, Kočenda, and Vácha (2015) demonstrated that positive and negative volatility shocks generate different degrees of market connectedness within the U.S. equity market. Their findings indicated that adverse market news generally produces stronger spill over effects than favourable information, reflecting investors' asymmetric responses to uncertainty. This asymmetry has important implications for intraday traders because risk transmission intensifies during periods of market stress, requiring dynamic adjustment of trading strategies and risk exposure.

Methodological developments continued with Baruník and Křehlík (2018), who introduced a frequency-domain connectedness framework capable of decomposing volatility spill overs into short-, medium-, and long-term components. Unlike earlier time-domain models, this approach revealed that connectedness varies across investment horizons, allowing researchers to distinguish between temporary market disturbances and persistent systemic risk. The frequency-based methodology has become particularly valuable for intraday trading research because short-term spill overs often dominate trading decisions during active market sessions.

Recognizing that market relationships evolve continuously, Antonakakis, Chatziantoniou, and Gabauer (2020) extended the connectedness literature by developing a time-varying parameter vector auto regression (TVP-VAR) framework. Their approach eliminated the need for arbitrary rolling-window estimation and provided smoother, more accurate estimates of dynamic market connectedness. The TVP-VAR methodology captures rapid changes in information transmission during financial crises, geopolitical events, and periods of heightened uncertainty, making it especially suitable for analysing modern electronic markets characterized by continuous information flows.

Research has also expanded beyond equity markets to examine volatility spill overs across multiple asset classes. Tiwari, Cuñado, Gupta, and Wohar (2019) investigated spill overs among global financial assets using both time- and frequency-domain analyses. Their findings demonstrated significant interconnectedness among equity, commodity, bond, and foreign exchange markets, particularly during episodes of elevated market volatility. The study highlighted that cross-market interactions have become increasingly important for portfolio diversification and intraday risk management as financial globalization continues to intensify.

Commodity markets have received increasing attention within the spill over literature due to their growing financialization and integration with broader financial markets. Ben Ameur, Ftiti, and Louhichi (2021) examined intraday spill overs among commodity markets and reported that information transmission becomes considerably stronger during periods of economic uncertainty and market turbulence. Energy commodities were identified as major transmitters of volatility, while agricultural commodities exhibited comparatively lower systemic influence. Their findings suggest that intraday commodity traders should account for cross-market information flows when constructing trading strategies and managing portfolio risk.

4.4 Machine Learning, Deep Learning, and Reinforcement Learning in Intraday Trading

The rapid advancement of artificial intelligence (AI) has fundamentally transformed intraday trading research by introducing computational techniques capable of identifying complex, nonlinear relationships within financial markets. Unlike traditional econometric and technical analysis models, machine learning algorithms are designed to learn directly from historical data, adapt to changing market conditions, and improve predictive performance through iterative optimization. The growing availability of high-frequency market data, advances in computational power, and improvements in cloud computing have accelerated the adoption of machine learning, deep learning, and reinforcement learning techniques in developing intelligent trading systems.

The earliest applications of computational intelligence to intraday trading primarily employed artificial neural networks (ANNs) for price prediction and market timing. Resta (2006) investigated the profitability of neural network-based scalping strategies and demonstrated that neural networks could successfully capture nonlinear price dynamics overlooked by conventional statistical models. The study highlighted the potential of AI-based systems to improve short-term trading performance, although practical implementation remained constrained by computational limitations and sensitivity to model parameters.

The integration of multiple machine learning algorithms marked the next stage in the evolution of intelligent trading systems. Kara, Boyacioglu, and Baykan (2011) compared artificial neural networks and support vector machines (SVMs) in predicting the direction of stock market index movements. Their empirical results indicated that both models substantially outperformed conventional statistical approaches, with artificial neural networks demonstrating slightly superior predictive accuracy. The study established machine learning as a viable alternative to traditional forecasting methods and encouraged further exploration of nonlinear predictive models in financial markets.

Recognizing that individual algorithms possess complementary strengths, researchers subsequently developed hybrid intelligent trading systems. Hossain, Shil, and Hossain (2014) proposed a hybrid machine learning framework that integrated multiple computational techniques to improve stock market timing decisions. Their results demonstrated that combining forecasting models enhanced predictive accuracy and reduced model-specific biases relative to standalone machine learning approaches. The study highlighted the importance of ensemble learning in financial forecasting, where market behaviour is inherently noisy, nonlinear, and continuously evolving.

Further advances were achieved by Patel, Shah, Thakkar, and Kotecha (2015), who emphasized the importance of feature engineering and data pre-processing in machine learning applications. Instead of relying solely on raw market data, they employed trend-deterministic data preparation techniques before applying machine learning algorithms. Their findings revealed that appropriate feature selection and pre-processing significantly improved forecasting accuracy, suggesting that data quality is often as important as algorithm selection. This study reinforced the growing consensus that successful AI-based trading systems require careful integration of financial domain knowledge with computational methodologies.

The emergence of deep reinforcement learning represents one of the most significant recent developments in intelligent intraday trading. Unlike supervised learning models that predict future prices, reinforcement learning enables trading agents to learn optimal trading policies through continuous interaction with the market environment. Sun et al. (2022) introduced DeepScalper, a risk-aware reinforcement learning framework specifically designed to capture fleeting intraday trading opportunities. The proposed model simultaneously optimized trade execution and risk management by learning from sequential market observations and adapting to changing market conditions. Experimental results demonstrated that DeepScalper outperformed several benchmark trading strategies across multiple evaluation metrics, highlighting the potential of reinforcement learning for dynamic portfolio management and real-time decision-making.

4.5 Intraday Trading Across Commodity, Foreign Exchange, and Cryptocurrency Markets

Intraday trading has expanded significantly beyond traditional equity markets, encompassing commodity futures, foreign exchange (Forex), and cryptocurrency markets. These asset classes differ in terms of trading mechanisms, liquidity, volatility, market participants, and regulatory frameworks; however, they share common characteristics that make them attractive for short-term trading. High liquidity, continuous information flow, leverage, and pronounced intraday price fluctuations provide abundant opportunities for traders employing technical analysis, quantitative models, algorithmic trading, and artificial intelligence. Consequently, researchers have increasingly examined whether intraday trading strategies can consistently exploit these market characteristics while accounting for evolving market microstructure and risk dynamics.

Foreign exchange markets represent one of the earliest and most extensively investigated environments for intraday trading research. Initial studies focused on evaluating the profitability of technical trading rules and determining whether exchange rates exhibited predictable short-term patterns. Taylor and Allen (1992) reported that technical analysis was widely employed by professional foreign exchange dealers, despite the prevailing belief in market efficiency. Their findings suggested that practitioners considered chart-based techniques valuable for identifying short-term market trends and supporting trading decisions.

Subsequent empirical research strengthened this evidence. Levich and Thomas (1993) employed bootstrap methodologies to demonstrate that selected technical trading rules generated statistically significant profits in foreign exchange markets, challenging the strict interpretation of the Efficient Market Hypothesis. Similarly, Curcio, Goodhart, Guillaume, and Payne (1997) analysed high-frequency foreign exchange data and found that certain technical trading rules produced profitable signals under specific market conditions, although profitability varied across currencies and market environments.

The literature gradually shifted from evaluating technical indicators toward understanding the mechanisms underlying exchange rate movements. Danielsson and Payne (2002) demonstrated that real trading activity and transaction patterns significantly influence short-term exchange rate dynamics, while Evans and Lyons (2002) established that order flow constitutes a major determinant of exchange rate fluctuations. Their findings highlighted that price discovery in foreign exchange markets is strongly influenced by trading activity rather than solely by publicly available macroeconomic information.

Market microstructure research further advanced the understanding of intraday foreign exchange trading. Osler (2003) explained the predictive success of technical analysis by demonstrating that clusters of stop-loss and take-profit orders generate predictable exchange rate movements. Cheung, Chinn, and Marsh (2004) complemented these findings by showing that foreign exchange professionals integrate both fundamental and technical information when making trading decisions. Menkhoff and Taylor (2007) reinforced the continuing importance of technical analysis, concluding that despite advances in quantitative finance, technical trading remains deeply embedded in professional foreign exchange practice.

Subsequent research increasingly emphasized market adaptability and evolving trading dynamics. Neely, Weller, and Ulrich (2009) provided empirical support for the Adaptive Markets Hypothesis by demonstrating that the profitability of foreign exchange trading strategies changes over time as market participants learn and adapt. Frömmel and Lampaert (2016) further showed that the effectiveness of technical trading strategies depends substantially on data frequency, indicating that intraday trading performance is sensitive to market sampling intervals. More recently, Orquín-Serrano (2020) proposed adaptive candlestick recognition models for the EUR/USD market, demonstrating that dynamically adjusted technical patterns outperform conventional fixed-rule approaches under changing volatility regimes.

Commodity futures markets have also received considerable attention because of their importance in global trade, hedging, and speculative activity. Martell and Trevino (1990) provided one of the earliest analyses of intraday commodity futures prices, documenting systematic intraday price behaviour that suggested opportunities for short-term trading. Their work established a foundation for subsequent investigations into commodity market efficiency and price discovery.

Research during the following decades increasingly focused on momentum and trend-following strategies. Marshall, Cahan, and Cahan (2008) demonstrated that quantitative market timing strategies could generate profitable trading opportunities in commodity futures, although performance varied across commodities and market conditions. Szakmary, Shen, and Sharma (2010) re-examined trend-following strategies and found that momentum effects persisted across numerous commodity markets, supporting the continued relevance of technical trading approaches.

The robustness of momentum strategies was further confirmed by Narayan, Ahmed, and Narayan (2015), who reported significant profitability of momentum-based trading in commodity futures markets. Han, Yang, and Zhou (2016) likewise identified exploitable trends across commodity prices, although they emphasized that market efficiency has gradually improved over time, reducing abnormal profit opportunities. These findings indicate that while momentum remains an important feature of commodity markets, strategy performance increasingly depends on market conditions and execution quality.

Recent studies have expanded commodity trading research beyond traditional technical analysis by incorporating market connectedness and behavioural perspectives. Hu, Mallory, Serra, and Garcia (2018) investigated price discovery between nearby and deferred commodity futures contracts, demonstrating that information transmission varies across commodity types and storage characteristics. Ben Ameur, Ftiti, and Louhichi (2021) examined intraday spill overs among commodity markets and found that volatility transmission intensifies during periods of economic uncertainty, particularly within energy markets. More recently, Laubsch, Smales, and Vo (2024) showed that traders' decisions are significantly influenced by 52-week high and low price levels, highlighting the importance of behavioural reference points in commodity futures trading. Robe, Raman, and Yadav (2024) further demonstrated that increasing financialization has improved liquidity while strengthening market interconnectedness, thereby altering the structure of modern commodity trading. Lauter, Prokopczuk, and Trück (2026) concluded that electronic trading and financialization have fundamentally transformed commodity market microstructure by accelerating information transmission and increasing trading efficiency.

The emergence of cryptocurrencies has introduced a new frontier for intraday trading research. Unlike traditional financial markets, cryptocurrency markets operate continuously, exhibit exceptionally high volatility, and provide abundant high-frequency trading opportunities. Consequently, they have become an ideal environment for studying algorithmic trading, market microstructure, and artificial intelligence.

Early cryptocurrency research concentrated on market efficiency and persistence. Caporale, Gil-Alana, and Plastun (2018) reported evidence of persistence in cryptocurrency returns, indicating departures from weak-form market efficiency. Phillips and Gorse (2018) employed wavelet coherence analysis to identify the major drivers of cryptocurrency price movements, emphasizing the importance of investor sentiment and market interconnectedness.

Subsequent studies increasingly focused on cross-market relationships and trading opportunities. Corbet, Lucey, Urquhart, and Yarovaya (2019) provided a comprehensive review of cryptocurrencies as financial assets and highlighted their distinctive risk-return characteristics. Ji, Bouri, Lau, and Roubaud (2019) demonstrated significant dynamic connectedness among cryptocurrency markets, indicating rapid transmission of shocks across digital assets. Yang, Göncü, and Pantelous (2018) examined momentum and reversal strategies in Chinese commodity futures, while Jin, Wang, and Yang (2020) identified statistically significant intraday momentum effects in Chinese futures markets, reinforcing the continuing importance of short-term price persistence.

The application of artificial intelligence and high-frequency trading has further accelerated cryptocurrency research. Petukhina, Reule, and Härdle (2021) documented distinctive high-frequency trading patterns within cryptocurrency exchanges, reflecting the growing influence of automated trading systems. Ghosh and Kanjilal (2024) demonstrated that advanced statistical techniques improve cryptocurrency pairs trading performance relative to conventional approaches. Jasiak and Zhong (2024) analysed both daily and intraday cryptocurrency dynamics, revealing substantial differences in volatility persistence across time horizons. Brauneis, Mestel, and Theissen (2025) identified systematic intraday trading patterns across global cryptocurrency exchanges, while Moser and Brauneis (2026) demonstrated that adaptive candlestick recognition combined with statistical learning techniques significantly improves short-term cryptocurrency price forecasting.

5. Comparative Analysis of Existing Studies, Research Gaps, and Future Research Agenda

The chronological and thematic review of 81 studies across five themes published between 1990 and 2026 demonstrates the remarkable evolution of intraday trading research from traditional technical analysis to sophisticated artificial intelligence-driven trading systems. While the literature has expanded considerably in terms of theoretical perspectives, methodological approaches, and market coverage, several inconsistencies and unresolved issues remain. A comparative examination of existing studies provides valuable insights into the strengths and limitations of current knowledge while identifying promising directions for future research.

One of the most evident developments is the transition from rule-based technical trading strategies to data-driven intelligent trading systems. Early studies primarily focused on evaluating moving averages, candlestick patterns, momentum indicators, and trend-following strategies under the assumption that historical prices contain exploitable information. Although several studies reported statistically significant abnormal returns, subsequent research frequently demonstrated that these profits diminish considerably after accounting for transaction costs, bid–ask spreads, slippage, taxes, and execution delays. Consequently, recent investigations have increasingly emphasized adaptive algorithms, machine learning, and reinforcement learning to overcome the limitations of traditional technical analysis.

The literature also reveals considerable variation in empirical findings across asset classes. Foreign exchange markets consistently exhibit strong evidence supporting technical analysis and order-flow-based trading because of their high liquidity and continuous trading environment. Commodity futures markets similarly demonstrate persistent momentum and trend-following opportunities, although profitability varies substantially across commodity sectors and market regimes. Cryptocurrency markets, in contrast, exhibit significantly higher volatility, stronger momentum effects, and greater market inefficiencies, providing abundant opportunities for intraday trading while simultaneously exposing traders to elevated risk. These differences indicate that trading strategies cannot be universally applied across asset classes without considering their unique institutional characteristics, liquidity conditions, and market microstructure.

Behavioural finance has become an increasingly important component of intraday trading research by demonstrating that psychological biases significantly influence trading decisions. Overconfidence, loss aversion, the disposition effect, anchoring, representativeness bias, and unrealistic perceptions of control consistently explain excessive trading activity and suboptimal investment performance across both developed and emerging markets. Nevertheless, behavioural studies remain largely isolated from quantitative trading research, with relatively few investigations integrating psychological variables into algorithmic trading models or artificial intelligence frameworks. This separation limits the development of comprehensive models capable of simultaneously explaining market behaviour and investor decision-making.

Although artificial intelligence has become one of the fastest-growing research areas, several methodological challenges remain unresolved. Many machine learning models operate as "black-box" systems whose internal decision-making processes are difficult to interpret. Consequently, high predictive accuracy does not necessarily translate into greater investor confidence or regulatory acceptance. Furthermore, financial markets are inherently non-stationary, causing prediction models trained on historical data to deteriorate when market conditions change. These limitations emphasize the growing importance of explainable artificial intelligence, adaptive learning systems, and continuous model updating.

The review also reveals substantial geographical imbalance within the existing literature. Most empirical investigations focus on the United States, Europe, Japan, China, and other developed financial markets, while comparatively limited evidence is available for emerging economies such as India. This imbalance is particularly significant because market efficiency, investor behaviour, regulatory environments, liquidity, transaction costs, and technological adoption differ considerably across countries. Consequently, findings obtained from developed markets cannot be generalized without empirical validation in emerging economies.

Another notable limitation concerns the evaluation of trading performance. A large proportion of studies measure forecasting accuracy, classification performance, or statistical significance without adequately assessing actual trading profitability. Measures such as prediction accuracy, root mean square error (RMSE), or mean absolute error (MAE) provide useful statistical information but do not necessarily indicate whether a trading strategy can generate sustainable profits after accounting for brokerage charges, taxes, bid–ask spreads, slippage, latency, and market impact. Future research should therefore place greater emphasis on economic significance rather than purely statistical performance.

The review further indicates that relatively few studies adopt an interdisciplinary perspective. Technical analysis, behavioural finance, market microstructure, volatility connectedness, artificial intelligence, and risk management are generally examined independently despite their strong conceptual interrelationships. Modern financial markets are increasingly characterized by algorithmic execution, behavioural responses, cross-market information transmission, and rapidly evolving technological infrastructures. Consequently, integrated theoretical frameworks are needed to explain intraday market behaviour more comprehensively.

In summary, the literature demonstrates substantial progress in understanding intraday trading over the past three decades. Research has evolved from evaluating simple technical trading rules to developing sophisticated artificial intelligence-driven trading systems capable of processing high-frequency financial data. Nevertheless, important theoretical, methodological, and empirical gaps remain. Addressing these limitations through interdisciplinary research, explainable artificial intelligence, realistic performance evaluation, and greater emphasis on emerging markets will significantly advance both academic knowledge and professional trading practice. These directions provide a robust foundation for the next generation of intraday trading research and offer valuable opportunities for developing more adaptive, efficient, and practically implementable trading strategies.

6. Conclusion

This study presents a comprehensive and systematic review of the evolution of intraday trading research by synthesizing 81 influential studies published between 1990 and 2026. The review demonstrates that intraday trading has evolved from a discipline primarily concerned with technical analysis and chart pattern recognition into a highly interdisciplinary field integrating behavioural finance, market microstructure, volatility connectedness, algorithmic trading, machine learning, deep learning, reinforcement learning, and high-frequency data analytics. This transformation reflects not only technological advancements in financial markets but also a growing understanding of the complex interactions among market participants, information flows, and intelligent trading systems.

The literature indicates that no single theoretical framework adequately explains intraday market behaviour. Traditional technical analysis continues to provide valuable insights into short-term price movements, particularly through trend-following strategies, momentum indicators, and price action techniques. Behavioural finance complements these approaches by explaining how psychological biases such as overconfidence, loss aversion, anchoring, and the disposition effect influence trading decisions and contribute to temporary market inefficiencies. Simultaneously, market microstructure research has demonstrated that order flow, liquidity, bid–ask spreads, and price discovery mechanisms play fundamental roles in shaping intraday price dynamics.

The review further highlights the growing importance of volatility spill over and financial connectedness research in understanding systemic risk and cross-market information transmission. Modern econometric methodologies, including vector autoregressive models, the Diebold–Yilmaz spill over framework, frequency-domain connectedness, and time-varying parameter vector auto regression (TVP-VAR), have significantly enhanced the ability to quantify dynamic interactions among financial markets. These developments have improved risk measurement and portfolio management while providing valuable insights for intraday trading across increasingly interconnected global markets.

Perhaps the most significant transformation has been the rapid adoption of artificial intelligence within intraday trading research. The progression from artificial neural networks and support vector machines to hybrid intelligent systems, deep learning architectures, and reinforcement learning frameworks demonstrates the increasing capability of computational models to identify nonlinear market relationships and adapt to changing market environments. Nevertheless, the review also indicates that improvements in forecasting accuracy do not necessarily translate into superior trading performance after considering transaction costs, slippage, market impact, taxes, and execution constraints. Consequently, the practical implementation of intelligent trading systems remains an important area requiring further investigation.

The comparative analysis also reveals several important research gaps. Existing studies are heavily concentrated in developed financial markets, whereas emerging economies—particularly India—remain relatively underexplored despite their expanding derivatives markets, increasing retail participation, and rapid adoption of electronic trading platforms. Furthermore, much of the existing literature examines technical analysis, behavioural finance, market microstructure, volatility connectedness, and artificial intelligence independently rather than integrating these complementary perspectives into unified trading frameworks. Such fragmentation limits the development of comprehensive models capable of explaining the multidimensional nature of intraday trading.

Another important finding is that many empirical investigations prioritize statistical forecasting accuracy over economic profitability. Measures such as prediction accuracy and forecasting error provide useful methodological comparisons but often overlook critical practical considerations, including brokerage costs, bid–ask spreads, liquidity constraints, execution latency, taxation, and risk-adjusted portfolio performance. Future research should therefore emphasize economically meaningful performance evaluation using realistic trading environments and transaction-level data.

Overall, this review demonstrates that intraday trading research has reached a stage where interdisciplinary integration is essential. Future advances are likely to emerge from hybrid frameworks that combine technical analysis, price action trading, behavioural finance, market microstructure, volatility connectedness, explainable artificial intelligence, and adaptive machine learning algorithms. Such integrated approaches have the potential to improve forecasting accuracy, strengthen risk management, enhance trading efficiency, and provide more robust decision-support systems for both academic researchers and professional market participants.

By systematically reviewing more than three decades of scholarly contributions, this study provides a comprehensive overview of the intellectual development of intraday trading research while identifying the principal methodological advances, theoretical debates, and emerging research opportunities. It offers a valuable reference for researchers, practitioners, policymakers, and algorithmic traders seeking to understand the current state of knowledge and the future direction of intraday trading. The findings also establish a strong foundation for future empirical investigations aimed at developing intelligent, adaptive, and practically implementable intraday trading strategies capable of operating effectively within increasingly dynamic and technologically sophisticated financial markets.

Based on these observations, several promising avenues for future research emerge. First, researchers should develop hybrid intelligent trading systems that integrate technical analysis, price action trading, behavioural finance, market microstructure, volatility connectedness, and machine learning within unified decision-support frameworks. Such multidisciplinary models are expected to improve forecasting accuracy while simultaneously enhancing practical trading performance.

Second, greater attention should be devoted to explainable artificial intelligence (XAI) to improve the transparency and interpretability of algorithmic trading systems. Developing AI models whose decision-making processes can be understood by traders, regulators, and institutional investors will enhance their practical applicability and facilitate regulatory compliance.

Third, future studies should employ high-frequency transaction-level datasets incorporating order book information, liquidity measures, bid–ask spreads, and execution quality. Such datasets will allow researchers to evaluate trading strategies under realistic market conditions rather than relying solely on historical closing prices or aggregated return series.

Fourth, comparative cross-market investigations examining equities, commodities, foreign exchange, cryptocurrencies, and derivatives using common methodological frameworks would provide deeper insights into the transferability of trading strategies across asset classes. Such studies would also contribute to the development of diversified multi-asset trading systems capable of adapting to varying market environments.

Fifth, emerging markets—particularly India—deserve considerably greater attention. The rapid growth of retail participation, algorithmic trading, derivatives markets, and digital trading platforms provides unique opportunities to investigate intraday trading behaviour within developing financial systems. Empirical evidence from India remains relatively limited despite the country's increasing importance in global capital markets.

Finally, future research should evaluate trading strategies using comprehensive performance measures that incorporate profitability, risk-adjusted returns, drawdowns, transaction costs, taxes, market impact, execution latency, and portfolio diversification. Such an approach will improve the practical relevance of academic research and facilitate the translation of theoretical models into implementable trading systems.

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