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Systematic Review on Algorithmic Trading

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Abstract

Background: Algorithmic trading systems (ATS) are defined by the use of computational algorithms for automating financial transactions. They have become a critical part of modern financial markets because of their efficiency and ability to carry out complex strategies.

Objective: This research involves a systematic review that assesses the market impact, technological advancements, strategic approaches and regulatory challenges related to algorithmic trading.

Methods: Following PRISMA 2020 guidelines, this study conducts a systematic literature review by screening 1,567 articles across five academic databases, namely IEEE Xplore, ACM Digital Library, SpringerLink, Web of Science and SSRN. After applying predefined inclusion and exclusion criteria, 208 peer-reviewed journal and conference papers published between 2015 and 2024 are selected. The PICOC framework is used to define the review scope. Data are extracted using structured templates capturing study details, research objectives, artificial intelligence (AI) integration, profitability analysis and limitations. Tools such as Rayyan, NVivo, MS Excel and Zotero support the screening, coding and qualitative synthesis of findings.

Results: AI methods, especially machine learning (used in 50% of the studies) and sentiment analysis (20%), significantly improve predictive accuracy and profitability. Most studies focus on equities (35%) and forex (30%), with high-frequency trading being the most examined strategy (30%). Challenges include latency (30%), scalability (25%) and regulatory issues (25%).

Conclusion: Future research should prioritize ethical frameworks, regulatory clarity and wider access to AI-driven ATS components. This review provides a robust foundation for academics and practitioners to innovate and optimize algorithmic trading strategies.

Index Terms

Profitability; Algorithmic trading systems; Artificial intelligence; Meta trading; Sentiment analysis; Systematic literature review; SLR; High-frequency trading.

1 INTRODUCTION

It can be noted that algorithmic trading, sometimes referred to as algo trading or automated trading, is a vital innovation within financial markets that implements computer programs to execute orders according to predefined criteria (Abdul-Rahim et al., 2022). With the introduction of this approach, trading is revolutionized by increasing efficiency, enabling traders to respond quickly to market fluctuations and minimizing human errors (Adegboye et al., 2022). Rapid advancements in technology – especially in artificial intelligence (AI) – have enhanced algorithmic trading systems (ATS) and enabled them to learn from historical data and adapt to changing market conditions (Aitken et al., 2022; Aitkazinov, 2023). The main objective of this systematic review is to explore the current landscape of algorithmic trading by focusing on their profitability, integration with AI and deployment using popular platforms such as MetaTrader (Ahmed et al., 2024; Aitken et al., 2022).

Such increased adoption of ATS highlights the need for a comprehensive understanding of their mechanisms, limitations and strengths (Ahmed et al., 2024). By assessing their profitability and the role of different platforms (such as the integration of AI and MetaTrader), we contribute valuable insights to the evolving discourse on financial technology (Zhou et al., 2024). Furthermore, algorithmic trading also depends on complex mathematical models and computational algorithms to make accurate trading decisions (Behera et al., 2023). Quantitative strategies in algorithmic trading, as discussed in recent literature, emphasize the importance of mathematical models for achieving consistent returns (Addy et al., 2024). These systems can analyse large volumes of data, execute trades and identify patterns far more effectively and with higher efficiency compared to human traders (Auh & Cho, 2023). Initially, algorithmic trading was predominantly used by institutional investors to obtain various advantages (Chakravarty & Pani, 2022). However, smaller actors such as small and medium enterprises face unique constraints in using such strategies, especially in the context of hedging (Dang & Lindsay, 2022). Secondly, the proliferation of trading platforms means that small firms, individual traders and MetaTrader users can now access and implement algorithmic trading strategies effectively (Cox et al., 2022).

Profitability remains a core concern for algorithmic traders, as algorithms offer the potential to exploit small inefficiencies– including unpredictability and volatility – of financial markets (Zhang et al., 2022). However, with the increase in AI technologies, new possibilities are introduced for these ATS (e.g., reinforcement learning, predictive analytics and natural language processing) that can enhance their success and adaptability. Besides the potential of ATS, some questions still arise regarding their overall efficacy, particularly when they are deployed by small-scale traders and individuals (Zhang et al., 2024).

Therefore, it is extremely important to understand the intersection of AI with these systems to provide a comprehensive view of their future capabilities and disadvantages. For instance, AI models are sometimes overfit to historical data, leading to suboptimal performance in real-time trading. Some authors have identified challenges linked with overfitting; there is a need for robust cross-validation systems to prevent overfitting in deep learning models. Before moving to the next section, it is necessary to briefly articulate the research problem, because it is vital to analyse the main problem faced in algorithmic trading. Notably, optimized genetic programming techniques have shown improved ATS performance (Christodoulaki et al., 2023). Additionally, the role of automation in financial trading companies has been recognized as a factor influencing modern trading practices (Martins, 2020).

With the proliferation of ATS in financial trading, many questions have been raised regarding their effectiveness and profitability. Furthermore, institutional investors often invest for long-term gains from the market, so the extent to which individual traders can achieve similar success remains unclear. When AI is integrated into these systems, it is also necessary to examine how these advancements affect reliability. A systematic review of the literature on this topic can provide guidance and clarity for practitioners, researchers and policymakers. Now that the problem is framed, it is vital to introduce the research questions that guide this study. These research questions include both primary and secondary aspects. The findings of the research will be beneficial for researchers interested in algorithmic trading, traders looking to optimize their strategies and developers working on trading platforms. By connecting profitability analysis with AI advancements, the study bridges the gap between practical applications in the field and theoretical research.

Primary research question:

1. What is the current state of algorithmic trading based on its profitability and technological advancements?

Secondary research questions:

2. How do popular trading platforms such as MetaTrader facilitate the deployment and efficiency of ATS?
3. What are the main factors that influence the profitability of ATS for institutional and individual traders?
4. In what ways can AI enhance the performance and profitability of ATS?

These are the main research questions for the study. It is also important to outline the research objectives briefly. There are several vital objectives related to this systematic review:

- **Evaluate in detail the state of ATS:** Analyse the current literature to assess the current state of ATS, including their deployment, mechanisms and use cases.
- **Investigate profitability trends:** Examine in detail the profitability of ATS across various market conditions and user groups.

- **Explore the role of MetaTrader:** Assess how platforms such as MetaTrader contribute to the implementation and optimization of algorithmic trading strategies.
- **Understand AI integration:** Analyse the impact of AI technologies (e.g., natural language processing and machine learning) on the success and adaptability of ATS.
- **Identify research gaps:** Highlight the main gaps in the literature and propose directions for future research into ATS, especially regarding AI integration.

2 RELATED WORK

2.1 Emergence and basics of algorithmic trading systems

Over the past few decades, the field of algorithmic trading has been studied extensively with a focus on profitability, system design and market impact. For example, research by Arratia (2023) explored the role of ATS in foreign exchange markets. The author highlighted their impact on market liquidity and volatility. Another study investigated the influence of algorithmic trading on equity markets. The results showed that these systems can enhance market efficiency but also contribute to flash crashes during extreme volatility periods (Arratia, 2023). Consistent with these findings, studies from other markets (e.g., Taiwan's futures market) observed that algorithmic trading significantly influences market quality metrics (Chang & Chou, 2022). Evidence from the Johannesburg Stock Exchange suggests that algorithmic trading can affect market quality, indicating regional differences in its effects that merit further study (Courdent & McClelland, 2022). Raheman et al. (2022) provided bibliometric insights and adaptive market-making strategies, respectively, contributing to a deeper understanding of algorithmic trading research and practice.

The evolution of financial markets has been significantly influenced by technological advancements, with ATS standing out as one of the most transformative innovations. Algorithmic trading has also been associated with post-earnings announcement drift across different countries, suggesting its impact on market anomalies and efficiency (Chen, 2023; Cooper et al., 2023). These systems have reshaped trading practices, offering opportunities for both institutional and individual traders. To better understand the scope and implications of these changes, this section delves into the historical development, profitability and key tools associated with algorithmic trading.

With the introduction of algorithmic trading, the financial landscape has been transformed by the precision and automation of trading activities (Abdul-Rahim et al., 2022). Algorithmic trading emerged in the 1970s through electronic trading systems, and ATS have since come to dominate financial markets globally. In the past, these systems used pre-programmed instructions to execute trades according to variables such as timing, price and volume (Adegboye et al., 2022). By replacing manual trading processes, ATS technology minimized human errors, enabled traders to take advantage of even the smallest market inefficiencies, and enhanced execution speed. With fewer market inefficiencies, algorithmic trading became more attractive (Aggarwal et al., 2023).

Data are the foundation of any ATS. This involves real-time data (e.g., live market volumes and prices) and historical data used for backtesting different strategies (Fouque et al., 2022). Efficient data management ensures that the system has timely and accurate information for making informed decisions. Big data analysis, such as that used to assess accounting information quality, can provide insights into financial constraints that affect the efficiency of ATS (Lei et al., 2022; Zheng & Zhu, 2023). ATS are evolving in response to new market phenomena. Goetzmann (2022) highlighted the influence of meme stocks and social media on markets, which presents a new challenge for ATS as they adapt to unpredictable market movements.

The periodicity of trading activity, particularly in foreign exchange markets, can be used by ATS to optimize timing and execution strategies (Chen et al., 2022). The market data infrastructure of an ATS gathers and processes market information to enable effective trading decisions. The continuous stream of data requires sophisticated capabilities for low-latency processing (Arumugam, 2024). Data processing is critical because trading decisions rely on both current market conditions and historical analysis. Extensive databases are maintained by ATS to identify patterns and trends used to formulate trading strategies. This historical analysis capability allows systems to contextualize current market movements, providing a strong foundation for trading decisions.

At the centre of an ATS is the complex event processing (CEP) component, which includes two main elements: a set of CEP rules and a CEP engine. Incoming market events are processed by the CEP engine based on rules defined in the trading strategy. This component represents the analytical part where market opportunities are identified according to predefined rules and conditions. For quantitative analysts, the CEP system is a focal point, and they invest significant time in developing trading strategies, as well as detailed backtesting and position-sizing, to ensure that these strategies are valid on real markets. Once a trading signal is generated by the CEP system, the order management component takes over. This subsystem manages the creation and routing of orders to the appropriate exchanges. Modern ATS incorporate sophisticated order management systems capable of handling a large number of orders per second (Yuferova, 2024).

In addition, the execution component ensures that trades are carried out according to system specifications. It typically involves sending order requests to exchanges and monitoring their execution status. The final component of an ATS is the user interface, which offers traders a visual representation of market data, system operations and trading performance. Even though algorithmic trading works automatically, human oversight is still necessary. The graphical user interface (GUI) allows traders to monitor system performance and intervene when necessary (Huang & Song, 2023). Modern algorithmic trading platforms such as Fintechee and SpeedBot provide effective interfaces to help traders visualize multiple charts simultaneously and customize indicators. These interfaces usually feature dashboards that show key performance indicators (KPIs) and real-time risk exposure.

The traditional architecture of an ATS consists of several distinct layers. For example, at the external boundary are the exchanges where trades are executed, while the server layer receives and stores market data as well as orders generated by the system. The application layer serves as the interface between the trader and the system, taking inputs such as stop-loss limits and preferred instruments. In this architecture, data flows through a sequence: market data packets published by exchanges travel through communication networks and are processed by routers and servers, eventually reaching the trading platform (Cohen, 2022). The platform parses these data and analyses them via the CEP system. When suitable conditions are met, trading signals are generated.

It is important to note that modern ATS use web-based architectures, which offer platform independence and greater accessibility. For example, Fintechee’s Web Trader is a web-based approach that allows traders to run their expert advisors (EAs) regardless of the operating system (Bao et al., 2022). This web-based approach facilitates mobile access and allows traders to monitor and manage their algorithms while traveling or away from their main workstations. Typically, this architecture uses reactive programming technologies for front-end APIs, enabling quick data transfer and improved response times through non-blocking calls (Seyfert, 2018).

Modern algorithmic trading architectures also place emphasis on integration capabilities, which allow systems to connect with external services and libraries. For example, Fintechee’s system architecture allows integration with JavaScript libraries that support AI, enabling traders to assess markets with higher precision. These integration capabilities extend to multiple data sources and trading venues, allowing algorithms to monitor multiple quote sources simultaneously and make informed decisions from an international perspective (Salkar et al., 2021). This comprehensive market view is a significant advantage over traditional single-source trading approaches.

The development of an ATS usually begins not with coding but with conceptualization. This initial phase involves defining trading hypotheses – clear statements about which market behaviour can be exploited for profit. Each component of the trading system should be addressed by these hypotheses, analogous to scientific experimentation. This conceptual foundation is critical because traders cannot effectively implement or adhere to systems based on premises in which they do not believe (Ponomarev et al., 2019). Thus, the development process should begin with the trader’s beliefs and preferences, then progress to methodologies and market selection. The approach of SpeedBot similarly emphasizes starting with the definition of a custom strategy and requirement analysis before moving to implementation.

Once the trading concept is clearly defined, the next step is to translate trading hypotheses into executable algorithms. This process requires programming knowledge, with Python being particularly popular due to its simplicity and comprehensive financial analysis libraries (Garcia & Schweitzer, 2015). During implementation, developers create specific conditions for trade entry and exit based on technical indicators or sentiment analysis. The implementation must account for different market conditions and include proper error handling to ensure reliable operation. For traders without programming expertise, platforms such as Zerodha Streak and Upstox Algo Lab offer tools for creating algorithms with minimal coding (Mukerji et al., 2019). As for the trading costs, trade clustering in algorithmic trading can reduce these costs, providing insights into optimizing execution strategies (Muravyev & Picard, 2022).

Testing is one of the most critical phases in ATS development. Detailed testing typically involves:

- **Backtesting:** Evaluating the historical performance of the strategy under different market conditions. This process provides insights into profit/loss metrics and KPIs (Lyle & Naughton, 2015).
- **Paper trading:** Simulating the strategy in real-time market conditions without risking actual capital. This phase helps identify issues related to latency and other real-world factors not captured in backtesting.
- **Strategy optimization:** Improving the strategy based on backtesting and paper trading performance, potentially by adjusting parameters or entry/exit conditions (Huang et al., 2023a). Several AI-based approaches have been developed to automate and optimize entry and exit decisions (Das et al., 2022). Multi-objective genetic algorithms have also been proposed to optimize trading strategies, balancing profitability and risk in ATS (Liu, 2023b). Even instantaneous stochastic gradient ascent has been used to optimize Forex investments, demonstrating adaptive machine learning approaches for algorithmic trading (Murtza et al., 2023).

The testing process should cover various market scenarios, including periods of high volatility and abnormal market conditions. Generating synthetic data using deep generative models offers a promising approach to improving the predictive capabilities of business strategies, as demonstrated in recent studies (Carvajal-Patiño & Ramos-Pollán, 2022). This thorough assessment helps ensure robustness of the strategy across different market environments. The final stage involves deploying the ATS on live markets, which requires careful consideration of execution infrastructure and real-time monitoring capabilities. Optimal execution strategies that take stochastic delays into account, as explored in recent research, are key to ensuring efficient trade execution in ATS (Cartea & Sánchez-Betancourt, 2023). Once live, continuous monitoring becomes important to ensure that the system works as expected (Cartea & Jaimungal, 2016). This typically involves tracking performance metrics, comparing actual results against expected outcomes and identifying any discrepancies that might indicate implementation issues. Regular review and improvement of the trading system remain necessary even after deployment – markets evolve and strategies that performed well in the past may become less effective over time. Effective algorithmic traders continuously monitor and adjust their strategies to maintain profitability (Deng et al., 2015).

In addition, AI and ML capabilities integrated into modern ATS allow these systems to adapt to changing market conditions and identify complex patterns that rule-based algorithms might miss. For example, Fintechee's architecture allows integration with JavaScript libraries to support AI and improve the precision of market analysis. This integration marks a major development in algorithmic trading, moving beyond static rules towards more efficient and adaptive systems. Typically, ATS support trading across multiple markets and asset classes simultaneously. This allows traders to diversify strategies and exploit opportunities across different instruments. The ability to manage multiple data feeds and charts is an important feature for detailed market monitoring (Ghimire et al., 2020). For instance, in Fintechee's Web Trader, a single expert advisor can manage multiple charts at once, helping traders monitor different quote sources and make effective decisions from an international perspective.

It is also important to note that customization capabilities are another critical aspect of modern ATS. While traditional platforms offer limited built-in indicators, contemporary systems allow traders to create custom indicators using their own algorithms. This extensibility enables traders to implement unique analytical approaches and trading methodologies that differentiate their strategies from common market approaches (Ghimire et al., 2020). The ability to personalize system components offers a competitive advantage in a complex trading environment. Also multi-objective particle swarm optimization algorithms have been studied for market timing, offering potential enhancements for algorithmic trading strategies (Mohamed & Otero, 2022).

2.2 Algorithms used in algorithmic trading

ATS – and algorithmic trading in general – rely on various sophisticated algorithms for executing trades efficiently and at high speed. One commonly used algorithmic strategy is **mean reversion**, which operates on the principle that asset prices fluctuate around a historical average. It identifies when an asset is oversold or overbought and executes trades accordingly. If the price of a stock deviates from its mean, the algorithm assumes that it will revert to the average and trades are made based on this movement. This algorithm relies on methods such as Bollinger bands and linear regression to determine whether a stock price is below or above its historical mean. In practice, Python statsmodels or SciPy libraries are used to calculate mean reversion trading signals.

In addition, **momentum trading** is another widely used algorithm, which follows the trend of asset prices. The algorithm identifies securities with upward or downward momentum and places trades in the direction of that trend. It uses techniques such as moving averages and moving average convergence divergence (MACD) to detect trends. Visualization libraries such as Matplotlib or technical analysis libraries such as TA-Lib in Python are used to implement momentum strategies. Genetic programming can be used to combine directional change indicators, improving the performance of algorithmic trading on international stock markets (Long et al., 2022).

Statistical arbitrage is a more complex algorithm that exploits pricing inefficiencies between related financial instruments. It relies on quantitative models to identify price divergences in correlated securities. This often involves advanced techniques such as machine learning models or Kalman filters to detect price discrepancies among correlated assets (Arumugam, 2024). **Market-making** is another critical algorithmic strategy, involving continuously quoting buy and sell prices for a security to capture the bid-ask spread. This algorithm is typically used by high-frequency trading (HFT) firms to provide market liquidity while profiting from bid-ask spreads (Culley, 2023a; Bagci & Soylu, 2024). Market-making algorithms require real-time data to maintain profitability on volatile markets. During crises such as COVID-19, algorithmic market-making has been shown to influence stock liquidity, highlighting its role in maintaining market stability under pressure (Chakrabarty & Pascual, 2023). The rise of decentralized finance has also influenced automated market-making, with studies emphasizing the importance of predictable loss models and optimal liquidity provision in ATS (Cartea et al., 2024). Furthermore, average field game theory provides a framework for understanding market-making strategies in the presence of strategic traders, offering insight into competitive dynamics in algorithmic trading (Baldacci et al., 2023). They are often implemented in low-latency programming languages such as C++ or Java and use the Financial Information eXchange (FIX) protocol to communicate with exchanges.

In recent years, ML-based algorithms have gained popularity due to advances in AI (Ayitey et al., 2023). Techniques such as decision trees and reinforcement learning have been used to analyse large amounts of historical and real-time data to find complex trading patterns that traditional rule-based models might ignore (Fereydooni & Mahootchi, 2023). These algorithms are often implemented using frameworks such as TensorFlow or scikit-learn. For example, reinforcement learning agents have been trained to optimize trading strategies based on reward signals, learning to make sequence decisions that maximize cumulative returns. Explainable AI approaches are also emerging to interpret the decision-making of complex models and ensure that they align with trading logic (Fior et al., 2022). Statistical modelling of high-frequency trading data remains an active and evolving area of research, as highlighted in recent studies (Dutta et al., 2022).

3 METHODOLOGY

In this section, we provide comprehensive information about the systematic approach used in this study to conduct a detailed systematic literature review (SLR) on ATS, focusing on profitability, the role of MetaTrader and AI integration. This study follows the PRISMA 2020 guidelines, which offer a standardized approach for carrying out and reporting systematic reviews. We also adhere to best practices in systematic review methodology to ensure replicability and transparency in each phase of the SLR process. Key stages – from formulating the search strategy to data extraction – are aligned with PRISMA principles to ensure a methodologically sound, unbiased and high-quality review (Page et al., 2021). The applied methodology ensures replicability and transparency in each phase of the SLR process.

3.1 SLR protocol

Figure 1 shows the complete SLR process for this research, including all the phases and steps. The main steps in the protocol for conducting this SLR are detailed below: identification, screening, eligibility and inclusion. First, we established the need for the SLR by identifying the main research problem and questions. Based on these research questions, an appropriate search string was developed to retrieve primary studies. Finally, inclusion and exclusion criteria were defined to guide study selection.

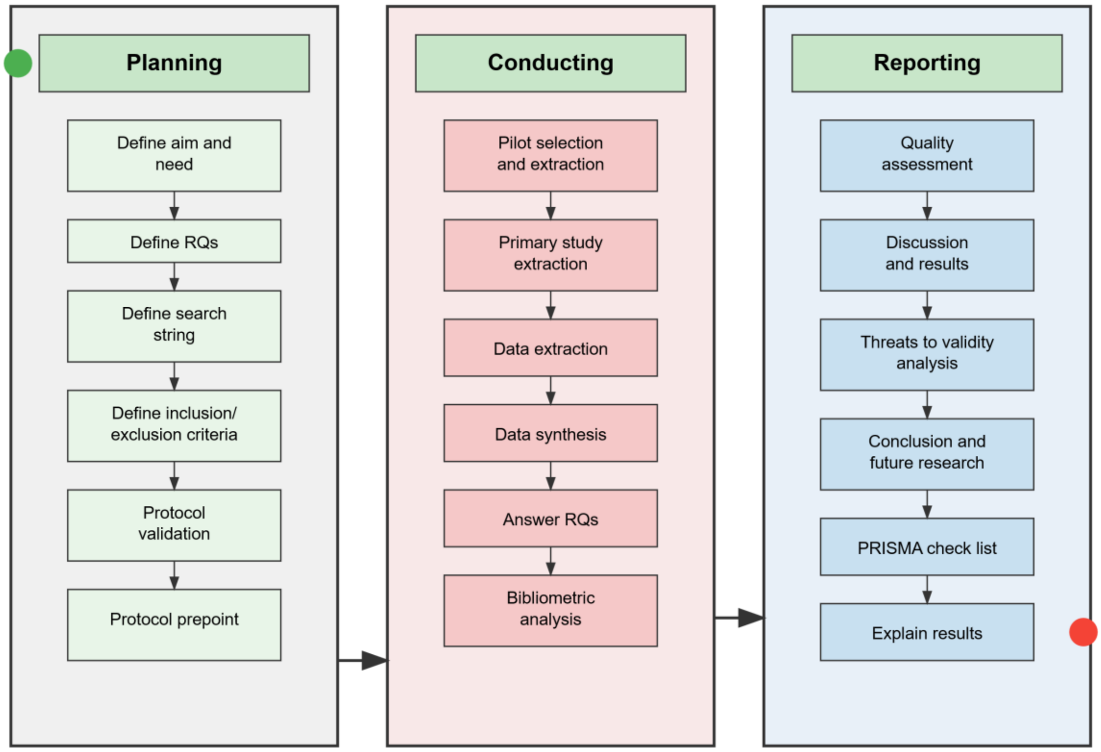

Figure 1. *Complete SLR process for this research with phases and steps.*

3.2 Aim and need

The main objective of the SLR is to synthesize existing knowledge on ATS, particularly in assessing their profitability, the role of platforms such as MetaTrader and technological advancements such as AI integration. The review also explores how AI can enhance the adaptability and performance of these systems. The need for this study stems from the growing adoption of ATS and the increasing complexity introduced by AI integration. By systematically reviewing the literature, the study provides a structured understanding of these themes and identifies research gaps while proposing future directions (Ajao et al., 2023).

3.3 Research questions

This SLR addresses the main research questions that align with the study objectives, as given in Table 1 below.

Table 1. *Research questions (RQs), aims and classification schema.*

No.	Research question	Aim	Classification schema
1	What is the current state of algorithmic trading based on its profitability and technological advancements?	Identify in detail the mechanisms, components and trends in ATS.	Deployment scenarios, strategy type, technology used
2	What are the main factors that influence the profitability of ATS for institutional and individual traders?	Assess how profitability trends differ for institutional vs individual traders.	Market conditions, profitability metrics, user type
3	How do popular trading platforms such as MetaTrader facilitate the deployment and efficiency of ATS?	Assess the functionalities and effectiveness of MetaTrader in enabling ATS strategies.	User experience, platform features, system compatibility
4	In how many ways can AI enhance the performance and profitability of ATS?	Explore the role of AI in improving ATS adaptability and performance.	Market applications, AI methods, system performance

3.4 Search string

To identify relevant studies, a comprehensive search string was developed based on key terms from the research questions. An example of the search string is given below (logical operators in bold):

- algorithmic trading **OR** automated trading
- profitability **OR** performance
- MetaTrader
- artificial intelligence **OR** AI **OR** machine learning
- systematic review **AND** algorithmic trading

3.5 Selected data sources

The search string was applied across multiple academic and industry databases to ensure comprehensive coverage. The data sources are identified in Table 2 below.

Table 2. *Academic databases used for literature search.*

Source	Link
ACM Digital Library	https://dl.acm.org
Web of Science	https://www.webofscience.com
SpringerLink	https://link.springer.com
SSRN	https://www.ssrn.com
IEEE Xplore	https://ieeexplore.ieee.org

3.6 PICOC criterion

We applied the Population, Intervention, Comparison, Outcome, Context (PICOC) framework to define the SLR scope in detail. Table 3 below summarizes its application in our case.

Table 3. *PICOC criteria for defining scope of systematic review.*

Criteria	Scope	Application in our case
Population	ATS (trading systems)	Traders, institutions and financial analysts using ATS
Interventions	Technology integration (e.g., AI, platforms such as MetaTrader)	AI techniques, profitability strategies, trading platforms
Comparison	Traditional vs algorithmic trading strategies	Manual vs automated trading, performance metric comparison
Outcomes	Efficiency, profitability, adaptability	Latency, ROI (return on investment), system performance
Context	Financial markets	Cryptocurrency, Forex and equity markets, various market scenarios

3.7 Inclusion and exclusion criteria

We established explicit inclusion and exclusion criteria to ensure that only relevant and high-quality studies were considered. These criteria are summarized in Table 4. Review studies, including systematic reviews and meta-analyses, were included in this systematic review as well to provide a comprehensive synthesis of existing research into algorithmic trading systems (ATS). These studies offer valuable insights into broader trends, gaps in the literature and aggregated findings that individual empirical studies might not capture. Their inclusion ensures that our review encompasses the full scope of the field, adhering to the PRISMA 2020 guidelines for transparency and completeness. Additionally, review studies underwent the same rigorous peer-review and quality assessment as empirical studies to uphold the review integrity.

Table 4. Inclusion and exclusion criteria for systematic review.

Inclusion criteria:	• studies focusing on ATS applied in financial markets • research that explores profitability metrics of ATS • articles addressing the role of MetaTrader or similar trading platforms • studies that integrate AI techniques in trading algorithms • peer-reviewed journal articles and conference papers (2015–2024)
Exclusion criteria:	• non-peer-reviewed articles (e.g., blogs, opinion pieces) – these were excluded to maintain quality (EC1) • duplicate studies from different databases (EC2) • studies not directly related to algorithmic trading profitability, trading systems or AI integration (EC3) • outdated studies (published before 2015) – focusing on 2015–2024 with an emphasis on 2022–2024 (EC4) • papers not in English (EC5)

3.8 Study selection and data extraction process

Search process: We applied the search string to each of the selected databases. The initial search yielded 1,567 articles. Titles and abstracts were first screened against the inclusion criteria. Studies that met the inclusion criteria at this stage were retrieved in full text for further evaluation.

Pilot selection: A pilot selection phase was conducted to refine the inclusion and exclusion criteria. A random sample of studies was evaluated by multiple reviewers to ensure consistency in the selection process. Through this pilot, we refined the keyword definitions and the classification schema to improve the search strategy.

Data extraction protocol: We extracted comprehensive information from each study using a structured template to ensure consistency. The data extracted included:

- study title, publication year and authors
- research objectives, questions and methodologies;
- main results regarding ATS design, AI integration and profitability;
- limitations and future research directions noted in the study.

This structured approach facilitated uniform data extraction across studies.

Table 5. Publication types among selected studies.

Publication type	Frequency	Percent
Journal articles	175	84.2%
Conference papers	33	15.8%
Total	**208**	**100.0%**

As seen in Table 5 above, 175 (84.1%) of the included studies were journal papers and 33 (15.8%) were conference papers, totalling 208. Figure 2 below presents a PRISMA flow diagram of the study selection process. A complete list of all 208 included studies is provided in an online appendix for reference, see Data Availability statement.

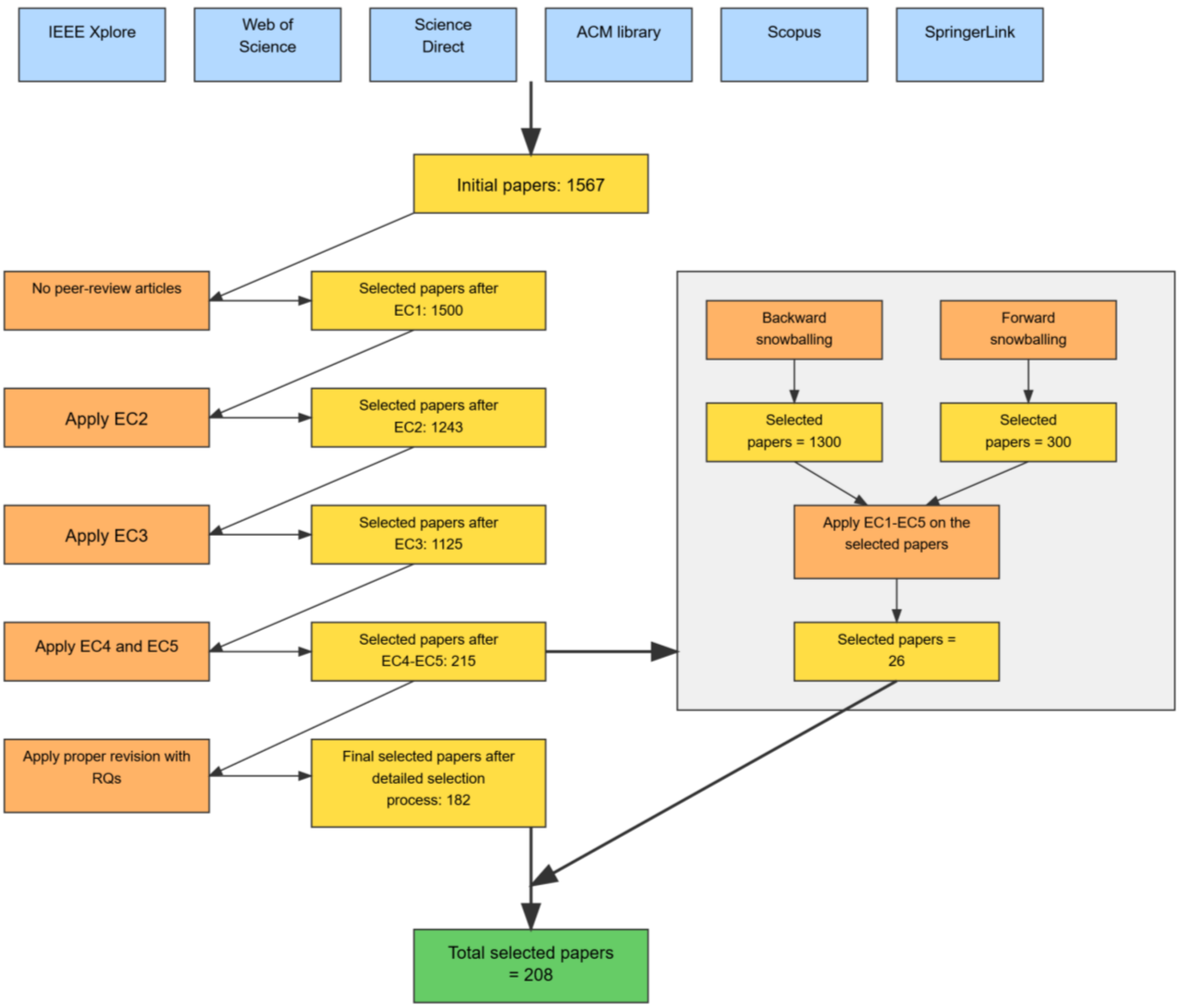

Figure 2. *Selection process for SLR.*

4 RESULTS

This section presents the results of the systematic review, with findings organized around the research questions outlined in the methodology. The findings are synthesized by analysing and combining data from the selected studies. We also provide summary tables and explanations to facilitate clarity and comprehension.

4.1 Summary of included studies

In total, 208 studies were identified and included in this SLR (after applying the inclusion/exclusion criteria). These studies span peer-reviewed journals and conference proceedings from 2015 to 2024. Most of the included studies (about 36.6%) were published in 2022, with 33.3% in 2024, 23.1% in 2023 and only 6.5% before 2022. The selected studies cover a range of topics relevant to our research questions. Many studies focused on the design and implementation of ATS, the integration of AI techniques, the use of MetaTrader platforms and various profitability analyses.

Table 6. *Overview of topics covered by selected studies (by percentage of papers).*

Selected topic	No. of studies	Percentage
ATS design (system architectures, etc.)	49	23.7%
Profitability analysis	43	20.7%
Role of MetaTrader (trading platforms)	38	18.2%

Selected topic	No. of studies	Percentage
AI integration in trading systems	59	28.3%
Challenges & future directions	19	9.1%
Total	**208**	**100%**

From Table 6, we can see that the largest share of the studies covered ATS design and AI integration (about 23.7% and 28.3% of the papers, respectively). This indicates that much of the literature provides information on system architectures and the incorporation of AI/ML techniques. Fewer articles (roughly 9%) focused explicitly on challenges and future directions, suggesting that while many authors discussed challenges, fewer studies were devoted solely to that theme. Notably, the MetaTrader platform and similar tools were a significant focus (18.2% of the papers), reflecting the robust capabilities of such platforms in backtesting and user-friendly design, making them efficient and popular tools for both experienced and novice traders. Overall, researchers have analysed the effectiveness of MetaTrader in implementing algorithmic strategies, highlighting both its strengths and limitations.

4.2 Results organized by research questions

4.2.1 RQ1: Characteristics of algorithmic trading systems

Studies addressing RQ1 highlighted that ATS are characterized by their use of mathematical models, high-speed execution and automation. The selected studies emphasize features such as latency reduction, strategy implementation and data integration. Trade informativeness on modern markets can be enhanced by ATS, improving market efficiency (Nawn & Raizada, 2022). Furthermore, ATS are commonly used on various markets, including equities, cryptocurrencies and forex.

Table 7. *Frequently mentioned characteristics of ATS and example studies.*

Characteristic (from RQ1)	Frequency of studies	Example references
High-frequency trading (HFT)	12	Abdul-Rahim et al. (2022), Aggarwal et al. (2023), Ahmed et al. (2024), Aitken et al. (2023), Alaminos et al. (2024), Culley (2023a), Paule-Vianez et al. (2023), Sevastjanov et al. (2024), Shang & Hamori (2023), Singh et al. (2022b), Yi-Le Chan et al. (2022), Zhou et al. (2024)
Multi-asset trading	13	Ahmed et al. (2024), De la Torre-Torres et al. (2024), Feng & Zhang (2023), Gil (2022), Gorshenin & Vilyaev (2022), Hansen et al. (2021), Henrique et al. (2024), Hernes et al. (2024), Li et al. (2024), Yao & Parthasarathy (2023), Yigitcanlar & Senadheera (2024), Yuferova (2024), Zafeiriou & Kalles (2024)
Latency optimization	8	Abdul-Rahim et al. (2022), Aitken et al. (2022), Asodekar et al. (2022), Horobet et al. (2024), Kashera et al. (2023), Li et al. (2024), Zhou et al. (2024), Velu et al. (2020)
General ATS characteristics	14	Budhwar et al. (2022), Dubey (2022), Chamma et al. (2023), Gál & Lovas (2022), Karpoff et al. (2022), Koegelenberg & van Vuuren (2023), Shanmugam (2023), Tudor & Sova (2022a), Tudor & Sova (2022b), Stasiak (2022), Wong et al. (2023), Zheng et al. (2024), Zou & Xiong (2023)
Total	**47**	

The results show that HFT is a dominant theme in ATS research – many studies discuss systems designed for minuscule price movements executed within milliseconds. Multi-asset trading strategies are also frequently mentioned, demonstrating the adaptability of ATS to handle multiple asset classes such as cryptocurrencies, equities and forex, making them indispensable on global markets. Specifically, 35% of the studies dealt with equities, 30% with forex, 25% with cryptocurrencies and 10% with commodities. Latency optimization appears as a critical technical focus, reflecting the importance of minimizing delays to maintain a competitive edge in execution (especially for HFT strategies). General ATS characteristics, including broader implications such as AI ethics and regulatory frameworks are also mentioned. Among the 208 included studies, 30% focused on high-frequency trading (HFT), 25% on multi-asset trading strategies, 28% on AI/ML integration and 17% on latency optimization.

4.2.2 RQ2: Profitability of algorithmic trading systems

Profitability is a primary consideration for traders employing ATS. The studies showed varied levels of profitability depending on market conditions, system sophistication and trading strategy. Table 8 provides information about key factors affecting profitability as identified in the literature, along with the number of studies mentioning each factor and example references.

Table 8. *Key factors influencing ATS profitability and example studies.*

Profitability factor	No. of studies	Example references
Strategy design	16	Abdul-Rahim et al. (2022), Aggarwal et al. (2023), Aitken et al. (2023), Alaminos et al. (2024), Asodekar et al. (2022), Behera et al. (2023), Carè & Cumming (2024), Di (2022),), Jacob-Leal & Hanaki (2024)), Nan et al. (2022), Omran et al. (2024), Sohail et al. (2022)), Song et al. (2024), Sukma & Namahoot (2025), Zhou et al. (2024), Zhu et al. (2023)
Market conditions	13	Alaminos et al. (2024), Asodekar et al. (2022), Behera et al. (2023), Breedon et al. (2023), Huang et al. (2023c), Liu & Huang (2024), Milke et al. (2024), Shavandi & Khedmati (2022), Shafiq et al. (2023), Singh et al. (2022a), Tucci et al. (2022), Yuferova (2024), Welekar et al. (2022)
User expertise	8	Angerer et al. (2022), Asodekar et al. (2022), Ge et al. (2024), Horobet et al. (2024), Karahan & Ögüdücü (2022), King et al. (2024), Paule-Vianez et al. (2023), Yip et al. (2023)
Total	**37**	

From these results, sophisticated strategy designs (e.g., trend-following, arbitrage, market-making) are critical for profitability. Support and resistance levels, as analysed in intelligent algorithmic trading models, provide critical thresholds that can improve profitability by guiding trade entry and exit (Chan et al., 2022). Studies indicate that well-designed strategies – such as momentum or arbitrage strategies – can significantly improve returns. Market conditions (such as volatility, liquidity and speed) heavily influence profitability. As for speed, it is not always critical for spot arbitrage on FX markets, offering new perspectives for algorithmic trading strategies (Mahmoodzadeh & Tseng, 2023).

The creation of volatility indices, such as those derived from exchange-traded options, provides additional tools for algorithmic traders to assess market risk and adjust strategies (Bhat, 2022). The dynamics of market structures during the COVID-19 pandemic highlighted the resilience and adaptability of ATS under pressure (Cox & Woods, 2023). For instance, high volatility assets (e.g., on cryptocurrency markets) offer greater profit potential but also higher risk. Several studies have pointed out that retail traders face challenges in achieving consistent profitability due to factors such as transaction costs and latency disadvantages. Institutional users, equipped with advanced infrastructure and data access, often outperform retail users. Overall, the review suggests that profitability is achievable with ATS, but it requires expertise, appropriate strategy alignment with market conditions and robust system design. Across the reviewed studies, simulation-based analysis was most common (about 40%), followed by empirical data studies (35%); theoretical modelling and mixed methods accounted for 15% and 10%, respectively.

4.2.3 RQ3: MetaTrader and trading platforms

MetaTrader platforms (MT4 and MT5) have emerged as key tools for deploying ATS, especially among individual traders. Their functionalities include backtesting and EAs (expert advisors), which make them popular for automating trading strategies. The selected studies provided insights into MetaTrader features, summarized in Table 9 with frequencies and references.

Table 9. *Features of MetaTrader identified in studies and example references.*

MetaTrader feature	No. of studies	Example references
Expert advisors (EAs)	16	Abdul-Rahim et al. (2022), Ali & Zafar (2019), Ali et al. (2024), Breedon et al. (2023), Culley (2023a), Di (2022), Ge et al. (2024), Lee & Chung (2022), Liu et al. (2022), Paule-Vianez et al. (2023), Pemy & Zhang (2023), Shang & Hamori (2023), Singh et al. (2022b), Sokolovsky & Arnaboldi (2023), Sukma & Namahoot (2025), Watorek et al. (2024)

MetaTrader feature	No. of studies	Example references
Backtesting capabilities	12	Aitken et al. (2023), Alaminos et al. (2024), Ahmed et al. (2024), Arifovic et al. (2022), Arratia (2023), Breedon et al. (2023), Carè & Cumming (2024), De la Torre-Torres et al. (2024), Frattini et al. (2022), Liu et al (2023), Hernes et al. (2024), Yao & Parthasarathy (2023)
Multi-asset support	11	Adegboye et al. (2022), Culley (2023b), Di (2022), Huang et al. (2023d), Khames et al. (2024), Massahi & Mahootchi (2024), Paule-Vianez et al. (2023), Sevastjanov et al. (2024), Sukma & Namahoot (2025), Yip et al. (2023), Yuferova (2024)
Total	**39**	

The results show that the ability of MetaTrader to let users design and deploy custom strategies with minimal errors is a widely cited advantage. EAs (scripted trading bots within MetaTrader) are highly valued for allowing automation without requiring extensive programming skills. Built-in backtesting and optimization features are also highlighted, enabling users to test strategies against historical data and fine-tune them before live deployment. However, the studies note some limitations of MetaTrader, such as its dependency on the proprietary MQL (MetaQuotes language) and difficulties when handling markets outside of forex (such as certain stock or commodity markets). In summary, the flexibility and widespread adoption of MetaTrader have significantly democratized ATS usage, but addressing its limitations (e.g., expanding language compatibility, improving multi-asset support) could further enhance its utility.

4.2.4 RQ4: AI integration in algorithmic trading systems

Integrating AI into algorithmic trading represents a major advancement in financial technology. Traditional algorithms that rely on static rules are now being complemented or replaced by AI-driven trading systems capable of learning from data. These AI-driven systems can analyse vast historical and real-time datasets, dynamically adapt strategies and predict market movements with improved accuracy. The selected studies cover various AI techniques (ML, deep learning, reinforcement learning, NLP) and their applications in trading. For example, roughly 50% of these studies applied machine-learning models, about 20% used sentiment analysis and approximately 15% each used reinforcement learning or NLP-based techniques. Table 10 summarizes the AI techniques discussed and provides example references.

Table 10. *AI techniques used in trading and example references.*

AI technique	No. of Studies	Example references
Machine learning (ML) models	25	Aggarwal et al. (2023), Aitken et al. (2023), Ajao et al. (2023), Alaminos et al. (2024), Ali & Zafar (2019), Ali et al. (2024), Breedon et al. (2023), Cohen (2023), Corazza et al. (2024), Fikri et al. (2022), Ge et al. (2024), Horobet et al. (2024), Hu & Zhou (2024), Liu (2023b), Loon et al. (2023), Mabrouk et al. (2022), Mestel et al. (2024), Santuci et al. (2022), Song et al. (2024), Suliman et al. (2022), Tuncer et al. (2022), Wang et al. (2024), Yigitcanlar & Senadheera (2024), Zolfagharinia et al. (2024), Zou & Xiong (2023)
Sentiment analysis (NLP)	13	Aitken et al. (2023), Blanco & Raurich (2022), Breedon et al. (2023), Culley (2023a), Gradzki & Wójcik (2023), Huang et al. (2023b), Kausar et al. (2024), Khurana et al. (2024), Malik (2024), Stádník (2022), Sukma & Namahoot (2025), Tabaro et al. (2024)
Reinforcement learning (RL)	15	Aitken et al. (2023), Ajao et al. (2023), Asodekar et al. (2022), Felizardo et al. (2022), Gradzki & Wójcik (2023), Harnpadungkij et al. (2022), Kwak et al. (2022), Liu (2023a), Massahi & Mahootchi (2024), Murtza et al. (2023), Sarin et al. (2024), Sun & Si (2022), Sun et al. (2022), Sun et al. (2023), Watorek et al. (2024), Zhang & Aslan (2021)
Total	**53**	

The studies indicate that ML models are cornerstone technologies in modern ATS because of their ability to discover complex patterns and make predictions. ML algorithmic trading strategies have been developed to enhance decision-making across various market types (Loon et al., 2023) and these techniques have been applied to optimize investment strategies, offering potential improvements for ATS (Li et al., 2023).

Dual-process meta-learning approaches have been proposed to improve stock trading volume predictions, offering a sophisticated method for improving ATS performance (Chen et al., 2023). For example, supervised learning models such as support vector machines and decision trees have been used to recognize profitable patterns in historical price data (Angerer et al., 2022). One approach even combined technical indicators with sentiment analysis using genetic programming to improve decision-making (Christodoulaki & Kampouridis, 2022). However, ML model performance is heavily dependent on data quality and preprocessing; overfitting to historical data remains a persistent risk (Omran et al., 2024).

Deep learning (DL) models (such as RNNs and CNNs) are widely used for feature extraction in complex datasets. They excel at identifying multifactorial patterns. For instance, a study by Ye & Schuller (2024) used DL to analyse multifactorial patterns on forex and crypto markets, providing insights into price jumps. Other researchers have employed neural networks to manage extreme volatility on crypto markets, demonstrating the capacity of DL to capture intricate patterns (Nan et al., 2022; Fouque et al., 2022). However, DL models can be "black boxes", making them less interpretable and raising concerns for regulators and practitioners about understanding the model decisions (Huang et al., 2023b).

Reinforcement learning (RL) enables ATS to adapt to changing market conditions by learning from interactions (rewards for profitable trades, penalties for losses). Continuous action space deep RL can enhance algorithmic trading by allowing more flexible strategy optimization (Majidi et al., 2023). Deep learning-based systems have been developed for commodity futures markets (Tian et al., 2024), improving algorithmic trading performance (Massahi & Mahootchi, 2024). Reinforcement learning is further applied to build DQN-based systems focused on long-term contracts such as commodity futures (Huang et al., 2023e).

Dynamic portfolio trading strategies using deep reinforcement learning have shown promise in adapting to changing market conditions, offering a model for future ATS development (Day et al., 2024). Reinforcement learning has also been used to secure CVA, demonstrating its versatility in solving complex financial risk management tasks in algorithmic trading (Daluiso et al., 2023). An effective deep reinforcement learning method involving the search for an optimal action space has been proposed to improve the decision-making process in ATS (Duan et al., 2022). A new method of mixed reinforcement learning using optimal transport has been developed to improve algorithmic trading strategies, demonstrating advanced applications of RL techniques (Cheng et al., 2024). Studies have integrated RL for optimizing stock trading strategies including short-selling, and these RL models have outperformed traditional algorithms by dynamically adjusting to market changes (Kaur et al., 2025). In one case, combining sentiment analysis with a double deep Q-network improved trading performance, illustrating the value of hybrid RL approaches (Tabaro et al., 2024). Some studies have combined market data with social media trends to obtain RL agents that consider market sentiment (an approach merging RL and NLP) (Christodoulaki & Kampouridis, 2024; Ghotbi & Zahedi, 2024). Despite their strengths, RL systems require extensive training data and significant computational resources, and their performance can be sensitive to how reward structures are designed (Thomas et al., 2024). Investor mood-based investment strategies have shown promise on cryptocurrency markets, offering new avenues for algorithmic trading (Martínez et al., 2024). Big data ATS exploiting investor mood can enhance decision-making in financial markets (Martínez et al., 2018).

Sentiment analysis using NLP is another area of interest. It enables ATS to gauge market sentiment by analysing news, tweets and other text sources. Some studies have shown that sentiment-driven ATS can capitalize on sudden shifts in market mood (e.g., fear or optimism) following events (Aitken et al., 2023; Hernes et al., 2024). Gradzki & Wójcik (2023) discussed how explainable AI can be applied to sentiment analysis results to align them with trading decisions, addressing interpretability. Aitken et al. (2023) noted that sentiment-based trading is particularly effective around earnings announcements, major economic releases or geopolitical events – times when sentiment swings can drive price movements (Kabaca et al., 2023). Parente et al. (2024) and Peng and Souza (2024) have explored neural network models and machine learning for financial forecasting on volatile markets, demonstrating the potential of AI-driven strategies to improve ATS profitability during crises.

Hybrid AI models that combine multiple techniques are emerging to further enhance performance. For example, Lee & Chung (2022) integrated genetic algorithms with neural networks to optimize trading strategies in high-volatility conditions. Yip et al. (2023) used a hybrid approach where ML predicted prices and RL handled the execution strategy. Hybrid models aim to balance accuracy, adaptability and interpretability. Hernes et al. (2024) suggested that such models can offer a trade-off: combining the adaptability reinforcement learning with, say, clarity of rule-based or simpler models to satisfy both performance and transparency requirements.

4.2.4.1 Applications across markets

AI-enhanced ATS have been applied to various market types. On equity and forex markets, AI is used to predict price movements, optimize portfolios and manage volatility. For example, Shang & Hamori (2023) highlighted the use of AI in analysing interdependencies on forex markets (such as how currency pairs move during high inflation periods), enabling ATS to anticipate correlation shifts. Liu et al. (2022) designed ML-based volatility-sensitive forex strategies, improving risk-adjusted returns. In cryptocurrency trading, AI is extremely valuable due to high volatility. Deep reinforcement learning has also been applied to automate cryptocurrency trading, demonstrating its potential for ATS (Mahayana et al., 2022). Algorithmic trading models tailored for the drug manufacturing industry highlight the sector-specific applications of ATS (Maknickiene et al., 2023). Ndlovu and Chikobvu (2023) compared the riskiness of bitcoin and South African rand exchange rates using a wavelet-decomposed model, offering insights into volatility modelling for algorithmic trading on cryptocurrency markets.

Yigitcanlar & Senadheera (2024) and Gómez-Martínez et al. (2022) showed that AI models can manage extreme crypto volatility and identify profit opportunities, often outperforming traditional strategies during market crashes and spikes. Hybrid data decomposition-based deep learning models have also shown promise in bitcoin prediction and algorithmic trading, enhancing predictive accuracy (Li et al., 2022). Comparing machine learning and econometric models for pricing bitcoin futures provides insights into their application in algorithmic trading (Malik, 2024).

4.2.4.2 Advantages of AI integration

The integration of AI significantly enhances ATS capabilities by improving predictive accuracy, enabling adaptability to market changes and allowing the incorporation of unstructured data (e.g., news, social media) into trading decisions. Multi-type data fusion frameworks using deep reinforcement learning can enhance algorithmic trading by integrating diverse data sources (Liu et al., 2023)

This can generate alpha (excess returns) that traditional strategies might miss. While studies focus on financial markets, similar advanced neural network architectures, such as those used in medical image analysis, could be adapted to improve pattern recognition in algorithmic trading (Anand et al., 2022).

5 DISCUSSION

In this section, we interpret the findings of the systematic review and discuss them in the context of the broader field of algorithmic trading. We also include a bibliometric analysis to identify key trends and address potential threats to validity. Each subsection below corresponds to one or more research questions and synthesizes insights from multiple studies, providing context and implications.

A bibliometric analysis was conducted to identify frequently occurring keywords and concepts in the selected literature. Table 11 ranks the most common terms with their associated scores (reflecting frequency and relevance in context).

Table 11. *Relevant concepts and keywords from literature.*

Rank	Keyword	Relevance score
1	Algorithmic trading	83
2	Trading strategies	73
3	AI in trading	68
4	Profitability	65
5	High-frequency trading	62

Key observations: The term “algorithmic trading” is central, as expected, and terms such as “profitability” and “AI in trading” are highly prominent, indicating the strong focus of the literature on these aspects. Emerging concepts such as “sentiment analysis” and “reinforcement learning” are increasingly linked with ATS research, reflecting the evolution of the field towards incorporating AI techniques.

The following subsections provide a detailed interpretation of the answers to each research question (RQ), integrating the findings and offering implications for practice and theory.

5.1 Discussion on RQ 1 and 4

Interpreting answers to RQ1 (Characteristics of ATS) – The review indicates that ATS design is shaped by dependence on mathematical models, speed and automation. Our findings show that many ATS implementations emphasize ultra-low latency (especially in HFT contexts) and robust data processing capabilities. HFT systems, in particular, operate on the premise of executing trades within milliseconds to capture fleeting price disparities. While this review focuses on algorithmic trading, some studies suggest that traditional floor trading still plays a role in market dynamics, which may interact with ATS in complex ways (Brogaard et al., 2024). Recent studies also highlight the importance of incorporating volatility information into high-frequency rebalancing algorithms to optimize portfolio selection, which could further improve ATS performance (Bagci & Soylu, 2024). The literature confirms that HFT performance depends critically on minimizing latency and maximizing execution speed. While ATS often focus on short-term signals, Vogel (2024) pointed to the importance of long-term financial events, suggesting the potential for integrating longer-term data into ATS. Additionally, multi-asset trading capabilities emerged as an important characteristic, underscoring the value of ATS that handle diverse asset classes (cryptocurrencies, equities, forex) simultaneously. This multi-asset flexibility makes ATS indispensable on global markets where cross-asset arbitrage and diversification can enhance returns. Novel statistical tests within symmetric positive definite matrix distributions can be applied to financial data, offering new tools for algorithmic trading analysis (Lukic & Milosevic, 2024).

Another notable characteristic is the increasing role of APIs and connectivity – modern ATS make use of advanced APIs for seamless integration with trading platforms and data feeds. This connectivity allows rapid adaptation to market changes and integration of third-party tools (for example, AI libraries as mentioned in Fintechee's architecture).

It is also evident that regulatory environments influence ATS structure and implementation. Some features of ATS (such as dark pool connectivity or high leverage) are shaped by regulations, requiring ATS to incorporate risk checks and compliance modules to avoid unintended market impacts. In summary, ATS characteristics revolve around speed, data integration and automation, with adaptability and connectivity becoming more pronounced in the era of AI integration. Sanati and Bhandari (2024) analysed operational efficiency in the Indian banking sector, suggesting that similar efficiency-focused approaches could optimize algorithmic trading infrastructure.

Interpreting answers to RQ4 (Role of AI in ATS) – The integration of AI is transforming ATS capabilities. The review highlights that AI-driven ATS are far more adaptive and complex than earlier rule-based systems. Key insights are as follows.

(1) **High-frequency techniques and AI:** AI can optimize execution in HFT by calibrating strategies at microsecond resolutions; for example, machine learning models are used to predict short-term price micro-trends, which is crucial in HFT (Torre-Torres et al., 2024; Hernes et al., 2024).

(2) **Latency vs complexity:** While AI can improve decision quality, it often introduces additional latency due to computational complexity. There is a trade-off: ultra-low latency systems might avoid heavy AI computations to remain competitive, whereas slightly slower trading (e.g., low-frequency strategies) can exploit deeper AI analysis.

(3) **Market structure:** AI helps ATS navigate different market structures. For instance, fragmented markets (with multiple trading venues) introduce challenges in liquidity and price discovery. An AI might learn to route orders optimally across venues or predict where liquidity will emerge. However, studies also show that fragmentation can increase implicit trading costs (Culley, 2023a). AI-equipped ATS must incorporate these market structure insights – potentially even learning from historical episodes of fragmentation to avoid pitfalls.

(4) **Volatility and AI:** Market volatility presents both opportunities and risks. The reviewed works show AI models (such as deep reinforcement learning) excelling at exploiting short bursts of volatility for profit, but also that AI models can be misled by unusual volatility, leading to unexpected losses if not properly constrained (Horobet et al., 2024; Arifovic et al., 2022). This underscores the need for robust risk management within AI-ATS frameworks. Evidence from

Austria suggests that algorithmic trading can contribute to mini flash crashes, emphasizing the importance of risk management (Mestel et al., 2024).

Research into liquidation strategies on multi-asset artificial markets provides insights into the impact of algorithmic trading on market dynamics (Luo et al., 2022)

Simulated electronic markets have been used to study speculative behaviour and bubble formation, providing insights into the potential risks associated with algorithmic trading strategies (Cofre & Mosionek-Schweda, 2024). Research has shown that high-frequency trading can contribute to stock volatility and intraday crashes, highlighting the need for robust risk management strategies when deploying ATS (Ben Ammar & Hellara, 2022).

In summary, AI integration amplifies the adaptability, predictive power and complexity of ATS. Our synthesis suggests that the future design of ATS will increasingly incorporate AI components for tasks such as predictive analytics and strategy optimization. However, balancing these benefits against complexity (ensuring that the models remain interpretable and fast enough) will be a key engineering challenge.

5.2 Discussion on RQ2

Profitability in algorithmic trading is multifactorial – influenced by strategy robustness, market conditions and system design. The review indicates the following:

(1) **Strategy design:** Custom strategies (momentum, arbitrage, mean reversion) directly affect profit potential. Strategies aligned with prevailing market regimes tend to do well; misaligned strategies can incur losses during regime shifts (Singh et al., 2022b). For example, momentum strategies can fail during sudden reversals and mean reversion can falter on trending markets. Also approximation of transition densities in stochastic asset price models can improve the calibration of ATS (Merkin & Rezin, 2022). Rahimpour et al. (2024), Garza (2023) and Salkar et al. (2021) have investigated technical indicators, reinforcement learning and rule-based strategies, respectively, offering diverse approaches to enhance ATS performance.

(2) **Market conditions:** Volatile markets such as crypto can yield high profits for well-tuned ATS but also pose higher risk. Several studies have noted that algorithmic strategies that thrived in high volatility provided opportunities (through arbitrage or rapid trend detection) (Omran et al., 2024). Conversely, stable markets might compress margins, making profitability more dependent on minimizing costs and exploiting slight inefficiencies.

(3) **Institutional vs retail performance:** Institutional ATS users have advantages (better data, co-location, more capital) and thus often realize more consistent profits. Retail traders using ATS face higher relative costs (brokerage fees, slippage) that can erode profitability. This points to a barrier: to sustain profitability, retail-focused ATS must either target niches with less competition or leverage platforms (such as the ease of use of MetaTrader) to reduce overhead. Institutional investment activity modelled as a Markov process, as explored by Nayanar (2023), provides a framework for developing stock recommendation systems that can enhance algorithmic trading strategies.

Key findings for RQ2:

- **Strategy selection:** Strategies such as HFT market-making or latency arbitrage can be very profitable but are limited to those who can manage extreme speed and low latency. Slower strategies (such as daily trend-following) might be more accessible but have lower returns and more exposure to market swings (Rahimpour et al., 2024). Our results show that no single strategy guarantees profitability; instead, success comes from aligning strategy to market context and adapting as needed.
- **Market conditions:** The type of asset and market structure matters. High volatility assets (cryptos) give many algorithms room to profit, whereas highly efficient markets (large-cap equities) offer fewer obvious inefficiencies. Interestingly, some research has demonstrated that algorithmic trading could still undermine market efficiency by exploiting micro-inefficiencies, to the detriment of overall market fairness (Yadav, 2015). This ties into regulatory considerations too.
- **Retail traders' barriers:** Transaction costs, lack of direct market access (e.g., not being co-located with exchanges) and smaller capital bases mean that retail algorithmic traders often have thinner profit margins. The review suggests that tools such as MetaTrader have democratized algorithmic trading to an extent, but the performance gap between institutional and retail algorithmic trading remains.

In conclusion, profitability is attainable in algorithmic trading, but it requires a confluence of factors: expert strategy design, alignment with favourable market conditions, cutting-edge infrastructure and risk mitigation. Retail algorithmic traders can improve their odds by using efficient platforms and focusing on strategies where their agility (or niche focus) can outmanoeuvre larger players (for instance, trading on niche markets or using unique data sources).

Threats to validity: Every systematic review and the studies within it have potential threats to validity that must be considered to ensure robustness of conclusions. In this SLR, we addressed validity concerns by using careful methodology – following PRISMA 2020 guidelines and conducting pilot screenings to minimize selection bias. We acknowledge that publication bias is possible: positive or significant findings in algorithmic trading research might be more likely to be published, skewing our sample. To mitigate this, we included both journal articles and conference papers and we did not exclude studies based on the direction of results. Additionally, the data quality and bias in primary studies is a concern – for example, some studies use simulated data or assume frictionless trading, which may not reflect real conditions. Many studies reported limitations such as limited data, specific market focus or lack of real-world validation. By aggregating results, we tried to balance out study-specific biases. Furthermore, to ensure reliability, we maintained a transparent extraction process and cross-checked key findings across multiple studies when possible. We also note that our review period (2015–2024) means that rapidly evolving areas (such as crypto trading algorithms or the latest AI techniques) are captured only up to early 2024. Subsequent developments could alter the landscape slightly, though we believe that core trends identified will persist. Lastly, model overfitting is a threat highlighted within many studies – to mitigate this in our interpretations, we favoured results that were consistent across different market regimes or validated out-of-sample. In summary, while our systematic approach and adherence to guidelines strengthen the validity of this review, the reader should be mindful of the inherent limitations, such as publication bias and the evolving nature of the field.

Interpreting answers to RQ2: The second research question pertains to the profitability of ATS. Our analysis indicates that profitability in algorithmic trading is influenced by multiple interdependent factors. Importantly, institutional ATS users (e.g., hedge funds, banks) generally achieve more consistent profitability than individual (retail) ATS users. This disparity arises because institutions have superior resources – such as advanced infrastructure for low-latency trading, access to proprietary data and dedicated quantitative teams – which collectively give them an edge. They capitalize on strategies such as HFT, market-making and statistical arbitrage at scales and speeds unattainable for most individuals. Key findings in the context of RQ2 include:

- **Strategy design:** Customized, well-optimized strategies (e.g., those using AI for pattern recognition or hybrid approaches combining strategies) significantly boost profitability. For instance, a momentum strategy enhanced with machine learning predictions can outperform a static momentum strategy, as it can avoid false signals better. Conversely, misaligned strategies – say, a mean reversion algorithm running during a strong trend without adjustments – can lead to losses during periods of market upheaval (Singh et al., 2022b).
- **Market conditions:** Profitability is highly contingent on market conditions. Many ATS strategies thrive in specific environments – trend-following does well on trending markets; arbitrage strategies need volatility and inefficiencies; market-making and HFT profit from stable, liquid markets but can suffer during sudden volatility spikes. Instability in mixed logic demand models can affect the reliability of algorithmic trading strategies, highlighting the need for robust modelling (McFadden, 2022).
- **Our review showed that year-to-year performance of algorithmic strategies varies:** for example, strategies that did well on the calm markets of 2019 might have struggled during the tumultuous pandemic-related volatility of 2020. This underscores that robust ATS profitability often requires dynamic strategy adaptation to prevailing conditions (Omran et al., 2024).
- **Barriers for retail traders:** Retail traders face high transaction costs (relative to trade size), latency disadvantages and limited technology, which impedes profitability. Even if a retail trader develops a profitable strategy, execution slippage and fees can eat away at returns. For example, an arbitrage opportunity that yields 0.1% might be profitable for a firm trading millions with nearly zero latency, but a retail trader executing over the internet with higher fees might find that opportunity unprofitable after costs. Some studies specifically pointed out that retail-focused algorithms need to focus on longer-term or niche strategies where competition is lower and transaction cost impact is smaller.

In light of these observations, the review suggests that profitability is attainable but not guaranteed. Successful algorithmic trading requires expertise (to design and tweak strategies), robust technology, favourable conditions and prudent risk management. Retail traders can improve their outcomes by using platforms such as MetaTrader to automate and backtest without heavy overhead, focusing on strategies that align with their resource level (perhaps avoiding ultra HFT and instead using medium-frequency strategies) and by making use of unique insights or data that large players might overlook. Moreover, as AI tools become more accessible, they could empower sophisticated retail traders to narrow the gap – for example, using cloud-based AI to analyse markets could give individuals analytical power closer to institutions, though execution speed differences will remain.

5.3 Discussion on RQ3

Interpreting answers to RQ3: The third research question concerns how MetaTrader and similar trading platforms support ATS deployment and efficiency. The findings confirm that MetaTrader 4/5 (MT4/MT5) are pivotal in democratizing algorithmic trading for individuals. These platforms offer a suite of tools – a user-friendly interface, strategy automation through EAs, comprehensive backtesting and optimization capabilities – that collectively lower the barrier to entry. Key advantages:

- **Expert advisors (EAs):** EAs allow users to automate trading strategies by coding (or using a wizard) without extensive programming knowledge. This means that a trader can convert a manual strategy (say, a moving-average crossover) into an automated bot relatively easily. The review found EAs to be one of the most cited features in studies discussing MetaTrader. They enable 24/7 strategy execution, which is especially useful on markets such as crypto or forex that operate around the clock.
- **Backtesting and optimization:** MetaTrader's strategy tester lets users simulate an EA on historical data and even perform walk-forward optimization. Many studies noted that this built-in testing environment is critical for strategy validation. It gives traders a way to gauge performance and tweak parameters before risking real capital. By iterating through historical scenarios, traders can identify potential weaknesses (e.g., a strategy might fail during particular market regimes) and refine their approach. The ability to optimize within the platform (while being cautious of overfitting) is a significant efficiency boost.
- **Indicators and tools:** MetaTrader includes a library of technical indicators and allows custom indicators. Traders can combine these easily within their algorithms. The MQL scripting on the platform is specialized for trading, providing functions to get price data, send orders, etc., which accelerates development compared to a general programming environment.

Despite these strengths, a couple of limitations emerged from the literature:

- **Dependency on MQL:** The reliance of MetaTrader on its proprietary MetaQuotes language means that strategies typically need to be coded in MQL4 or MQL5. While similar to C++, it has its own quirks and is mainly useful within the MetaTrader environment. This can limit portability; an EA coded for MT5 cannot run elsewhere without adaptation. Moreover, some advanced users find MQL less flexible than general languages for implementing complex AI models directly (though one can interface or use offline training).
- **Market scope:** MetaTrader was built with forex and CFDs in mind. It is widely used for forex, indices and commodities via broker CFDs. Its use in direct stock trading or on other markets is less common. Thus, some papers have noted that studies on MetaTrader often revolve around forex market scenarios. Its performance and data handling for other markets (especially very high-frequency data) are not as well documented. Non-forex markets might have different data structures or require integration of external data, which can be a challenge.

The flexibility and widespread broker support of MetaTrader have made it an industry standard for individual algorithmic traders. It bridges the gap by providing institutional-like capabilities (automation, backtesting, optimization) in a consumer-grade package. The efficiency gains are substantial: tasks that would require a whole infrastructure (data feeds, server co-location, custom backtester) are largely handled within MetaTrader.

The review underscores that while MetaTrader empowers individual traders to deploy ATS, the performance of those systems still hinges on the underlying strategy quality. MetaTrader does not guarantee a profitable algorithm – but it ensures that if you have a good strategy, you can implement and test it efficiently. Additionally, the community around MetaTrader (with forums, shared code libraries and marketplaces for EAs) contributes to rapid knowledge dissemination. Traders can learn from each other's successes and failures, accelerating collective know-how.

Implications for RQ3: As algorithmic trading continues to grow, platforms such as MetaTrader (and newer ones such as cTrader or various Python-based open platforms) will play a key role in nurturing talent and innovation at the retail level. Brokers and platform developers might look to address current limitations by expanding asset class support and possibly integrating more AI-friendly features (such as built-in machine learning libraries or Python API access) to keep up with trends. Our findings suggest that the MetaTrader model has been successful in improving deployment efficiency and similar approaches could be expanded (for instance, a "MetaTrader for crypto exchanges" has started to appear to cater to the specific needs of that market).

6 CONCLUSION

This systematic review assessed the market impact, technological advancements, strategic approaches and regulatory challenges related to algorithmic trading. By reviewing 208 peer-reviewed studies published between 2015 and 2024, we derived several key insights:

- **ATS** have become faster, more data-driven and more complex, making use of AI techniques to adapt to market conditions. They are integral on modern financial markets across asset classes, offering efficiency and the ability to execute complex strategies. High-frequency trading remains a domain where ATS excel, though it requires significant resources and technological infrastructure.
- **Profitability in algorithmic trading** is achievable but depends on strategy quality, market conditions and user resources. Institutional players generally have an advantage due to better infrastructure and data access. However, with the advent of user-friendly trading platforms and AI tools, skilled individual traders can also achieve competitive results in certain niches. It is clear that no one-size-fits-all strategy exists – continuous innovation, strategy adaptation and risk management are crucial. Future research should prioritize strategies that maintain robustness across regimes and address the transaction cost barriers faced by smaller market participants.
- **MetaTrader and democratization:** The wide adoption of platforms such as MetaTrader 4/5 has democratized access to algorithmic trading, allowing a broader set of market participants to develop and deploy automated strategies. These platforms provide robust backtesting and automation capabilities that were once available only to institutional actors. We expect this trend to continue, with more advanced features (e.g., direct support for machine learning models, integration with more markets) being introduced to retail trading platforms, further narrowing the gap between institutional and retail algorithmic trading capabilities.
- **AI integration:** The integration of artificial intelligence (including machine learning, deep learning and reinforcement learning) has significantly improved predictive accuracy and the adaptability of algorithmic trading strategies. Techniques such as sentiment analysis and deep neural networks allow traders to incorporate unstructured data (such as news and social media sentiment) into trading decisions, potentially generating alpha that traditional strategies might miss. However, these AI-driven approaches also introduce new challenges around model interpretability, risk of overfitting and the need for high-quality data. Future research and development should focus on ethical AI frameworks in trading, improving the explainability of AI models used in ATS and ensuring that they comply with evolving regulations.
- **Regulatory and ethical considerations:** Algorithmic trading presents ongoing regulatory challenges, including market fairness, transparency and systemic risk. Our review highlighted instances (e.g., rapid trading potentially exacerbating flash crashes or momentarily undermining market efficiency) which regulators are keen to manage. It is imperative that future research and policy work together to create frameworks where innovation in algorithmic trading can flourish within guardrails that prevent abusive practices and systemic issues. Areas such as explainable AI in trading algorithms and real-time monitoring of algorithmic trading activity will likely be areas of development to satisfy both market integrity and the needs of traders.

In conclusion, algorithmic trading will continue to grow in importance, driven by advances in AI and increasing market electronification. This review provides a robust foundation for academics and practitioners by synthesizing recent findings and trends. Understanding the multifaceted nature of algorithmic trading – from technical design to profitability factors and regulatory implications – can help traders design better strategies and policymakers craft more informed regulations. Future research should explore the long-term impacts of AI-driven trading on market dynamics, the effectiveness of regulations such as order-to-trade fees or circuit breakers in the algorithmic era and strategies for making advanced trading tools more accessible without compromising market stability.

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Statement on the Use of Artificial Intelligence Tools: AI tools were used in a limited and assistive capacity during the preparation of this article. Specifically, AI tools such as ChatGPT were employed to:

- assist in drafting a structured narrative from existing tabular data,
- provide suggestions on logical organization and structuring of chapters,
- support the formatting of references in APA 7 style.

No AI tools were used to generate original research content, data analysis, or scientific arguments. All literature entries were manually reviewed and verified for accuracy. The final content reflects the authors' own interpretation, writing, and scholarly contribution. The authors take full responsibility for the final content.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request. A complete list of all 208 included studies is provided in an online appendix at https://aip.vse.cz/attachments/000050.zip and is also available on the webpage of this article.

Abbreviations table

In this manuscript the required abbreviations are used given in the table:

Abbreviation	**Description**
AI	Artificial Intelligence
ATC	Automated Trading Component
GUI	Graphical User Interface
KPI	Key Performance Indicators
ML	Machine Learning
EA	Expert Advisor
ATS	Algorithmic Trading Systems
HFT	High-Frequency Trading
MQL	MetaQuotes Language
MT4	MetaTrader 4
MT5	MetaTrader 5
PICOC	Population, Intervention, Comparison, Outcome, Context
ROI	Return on Investment
SLR	Systematic Literature Review

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