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FINANCIAL TRADING TECHNOLOGICAL ADVANCEMENTS: SYSTEMATIC REVIEW

Introduction. *Transformations have drastically reshaped the landscape of financial markets, making it necessary to reassess current knowledge and future trends of financial trading technologies (FTT).*

Problem Statement. *The use of a variety of FTT requires to structure them depending on the level of machine technology and the level of trading strategy.*

Purpose. *To investigate the technological advancements in financial trading to assess the quality of scientific research and outline promising areas for further development.*

Materials and Methods. *By following the PRISMA 2020 standard, this systematic review covers 130 research articles (for 2013—2023) on FTT, focusing on technologies used. An innovative Four-Quadrant Theory was used to analyze the synergy between machine technology and trading strategy, which is based on 2 dimensions' total of 8 factors.*

Results. *Key financial technologies include algorithmic trading, machine learning, and deep learning, each with unique traits: speed, automation, adaptability, and complex pattern recognition. These technologies have improved market efficiency, risk management, and personalized trading strategies. The Four-Quadrant Theory offers a structured approach to understanding the interaction between machine technology and trading strategies and divides interactions into four quadrants.*

Conclusions. *The transformative impact of technological advancements in financial trading is evident. The main technologies have substantially improved market liquidity, trading efficiency, and risk management practices. The Four-Quadrant Theory lets to suggests that further exploration could lead to more intelligent, diversified trading systems, with data-driven decision-making and artificial intelligence playing pivotal roles. The importance of hybrid technology, scientific assessment of performance and the cutting-edge development of autonomous intelligent trading systems for the further study of financial trading technology were underscored.*

Keywords: risk management, financial market, FinTech, artificial intelligence, algorithmic trading, machine learning, deep learning.

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Financial trading, as a domain that has garnered considerable scholarly interest, has experienced substantial technological progress over the years. The integration of cutting-edge technologies into the realm of financial trading has not only revolutionized market structures and operations but has also posed new challenges and opportunities for market participants, regulators, and academics alike. The intricate interplay between technology and financial trading is evident in the rise of algorithmic trading, where complex mathematical models and computational algorithms execute trades with unprecedented speed and precision. These advancements have not only altered trading strategies but have also ushered in an era of high-frequency trading, characterized by rapid order execution and vast volumes of transactions. Furthermore, the integration of artificial intelligence and machine learning techniques has empowered traders with predictive analytics and adaptive decision-making capabilities.

As technological innovations increasingly shape the ways of trading activities, an in-depth analysis of these advancements becomes imperative for scholars, practitioners, and policymakers. To comprehensively study modern financial trading technology applications, in this paper, we aim to conduct systematic research on the topic of financial trading technology development through a systematic review. By synthesizing and critically evaluating existing research, this study aims to provide a comprehensive understanding of the transformative impact of technology on financial markets, elucidating the key trends, implications, and areas for future exploration.

In the era preceding the technological revolution (Traditional Trading Methods (Pre-2000)), the financial markets were dominated by traditional trading methods grounded in fundamental and technical analysis. Fundamental analysis [1], which assesses the intrinsic value of securities, drew from the seminal work of Graham and Dodd (1934), who established a systematic approach to evaluating stocks [1]. Similarly, Buffett (1958) expanded on these principles, applying value investing techniques to market operations [2]. On the technical side, pioneers like Edwards and Magee (1948) introduced methods to predict future market movements based on historical price patterns [3]. These practices largely relied on manual chart reviews and the expertise of traders to identify potential trading opportunities. Further contributions by Murphy (1986), who consolidated various technical indicators and charting tools into a comprehensive guide [4], provided traders with an enhanced toolkit for market analysis.

The inception of the 21st century heralded a revolution in financial trading with the introduction of algorithmic trading systems (The Advent of Algorithmic Trading (Post-2000)). Rule-based algorithmic trading became prominent, where trades were executed via algorithms defined by human-programmed rules [5]. These systems were designed to follow strategies based on traditional methodologies, quantitative models, or bespoke strategies crafted by seasoned traders. The work of Aldridge (2009) illustrates the efficiency and speed of these automated systems, significantly outperforming manual trading methods [6]. The transition was further underscored by the adaptation of mathematical models in finance, such as the Black-Scholes model for option pricing, which found new applications in creating rule-based trading strategies [7]. The advent of electronic trading platforms further facilitated the widespread adoption of algorithmic trading, as noted by Harris (2003), who discussed the market infrastructure changes that underpinned this shift [8].

The integration of machine learning (ML) into financial trading has revolutionized the field, providing systems capable of digesting vast amounts of data to make informed trading decisions. The categorization of ML into supervised [9], unsupervised [10], and reinforcement learning [11] has been a pivotal development. Supervised learning models, like Support Vector Regression (SVR), have been utilized for price prediction, with studies by Kim (2003) demonstrating their effectiveness [12]. Random Forest (RF), an ensemble learning method, was shown by Liaw and Wiener (2002) to be particularly useful for its robustness and ability to handle non-linearity in financial data [13].

The application of neural networks, such as Long Short-Term Memory (LSTM) networks, has been significant in dealing with the temporal sequences in financial time series. Works by Hochreiter and Schmidhuber (1997) introduced LSTMs, which have since been adapted for financial forecasting [14]. The versatility of neural networks in finance is further evidenced by the use of Fully Connected Neural Networks (FNNs) for pattern recognition and Convolutional Neural Networks (CNNs) for feature extraction from complex data structures, as illustrated in the research by O'Shea and Nash (2015) [15]. Recurrent Neural Networks (RNNs) by Rumelhart et al. (1986) have laid the groundwork for utilizing sequential data within trading algorithms, proving influential in the design of dynamic systems capable of learning from time-series data [16]. The advent of reinforcement learning (RL) and Deep Reinforcement Learning (DRL), particularly in the context of making decisions based on large volumes of data, has been detailed by Mnih et al. (2015), showcasing how DRL can tackle the challenges of financial trading environments [17].

AIMS AND OBJECTIVES

The overarching aim of this systematic review is to comprehensively investigate and synthesize the existing body of literature on technological advancements in financial trading. In pursuit of this aim and to guide the systematic exploration of the multifaceted relationship between technology and financial trading strategy, the specific objectives are as follows:

1. Trace the evolution of technological advancements in financial trading;
2. Assess the quality of existing research;
3. Identify Research Gaps and Propose Future Directions.

For achieving these tasks, the PRISMA 2020 standard, and an innovative Four-Quadrant Theory were used.

1. PRISMA 2020 STANDARD FOR SYSTEMATIC SCOPING REVIEW

A scoping review is a type of knowledge synthesis that uses a systematic and iterative approach to identify and synthesize an existing or emerging body of literature on a given topic [18]. It is useful to map the literature on evolving or emerging topics and to identify gaps [19]. The primary objective of this systematic review is to comprehensively analyze and synthesize scientific publications related to technology development in financial trading (FT) within the context of financial markets. To ensure a rigorous and scientifically valid approach, we adopted the PRISMA 2020 standard for conducting the systematic literature review (SLR) [9]. PRISMA is widely recognized for providing evidence-based guidelines to enhance the reporting and quality of systematic reviews. The review process comprises a 27-item checklist and a four-phase flow process that includes the following stages [20]: Identification, Screening, Eligibility and Inclusion.

Systematic reviews go beyond traditional literature reviews to encompass systematic, structured, and explicitly described steps of gathering and analyzing relevant existing knowledge [21—23]. To scientifically design the systematic review, the specific steps we have taken are as follows:

Step 1: Identifying the research question.

Defining the scientific range of the research question is a vital first step. A too-broad range will dramatically increase the number of papers for consideration, and a too-narrow range may compromise the breadth and depth of the review research.

Step 2: Identifying relevant studies.

Build the search strategy — keywords, Subject Headings, databases — and further refine the strategy based on the papers found.

Step 3: Selecting Studies to Be Included in the Review.

Define the inclusion and exclusion criteria, and finally determine the target studies. The actual screening of papers should consist of reading not only the title of the paper, but the abstract as well. If an abstract is not available, a full-text review of the paper is required.

Step 4: Charting the Data.

Develops the data extraction form based on the review articles database. The main categories of information will be listed, which are author, source, year, citations, research object and main results. These categories are vital for financial trading technology study and are usually popularly applied in scientific scoping review research [24, 25]. In addition, some technological categories are also considered in this systematic review.

Step 5: Collating, Summarizing, and Reporting the Results.

Once the data have been extracted from all papers, numerical and thematic analyses are conducted. The findings from the numerical analysis will be presented in a table to showcase the most salient aspects of the review.

To capture a comprehensive range of studies related to financial trading technology, we conducted an extensive search across the reputable academic database: Scopus (Version 2023/08) [26]. We utilized relevant keywords commonly associated with technological advancements in financial trading, such as ‘algorithm’, ‘model’, ‘prediction’ and ‘forecasting’. These carefully chosen keywords allowed us to focus exclusively on studies directly related to financial trading technology, avoiding unrelated topics. The initial search codes we set according to the topic relevance are as follows [26]:

TITLE-ABS (financial AND market AND trading AND (algorithm OR model OR prediction OR forecasting)) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE , “p”) OR LIMIT-TO (SRCTYPE , “j”)) AND (LIMIT-TO (OA , “all”)) AND (LIMIT-TO (DOCTYPE , “ar”)) AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (PUBSTAGE , “final”))

At the same time, to ensure the effective inclusion and exclusion of relevant studies within the review, and further promote transparency and accuracy in the findings, we established specific inclusion criteria (IC) to guide the selection of studies, which are detailed as follows:

IC1: Availability Online: This review considered only sources that were digitally available online, excluding works that were not published electronically.

Table 1. **Inclusion and Exclusion Criteria**

Inclusion criteria	Exclusion criteria
Publications during 2013—2023 (August) (IC5)	Publications before 2013 (IC5)
Publications in English (IC2)	Publications not in English
Publications as Journal articles (IC4)	Non-peer-reviewed publications, e.g., preprint and dissertations
Publications in non-predatory journals (IC6)	Publications in predatory journals
Publications available online (IC1)	Publications unavailable online
Empirical research output except for preprints and dissertations (IC3)	Non-empirical research outputs, e.g., conceptual papers
‘Trading’ searching outputs, e.g., exemplified in their titles, keywords, abstracts (Not an IC)	Non-‘Trading’ searching outputs

Source: generalization by the authors.

IC2: Language of Publication: The inclusion was limited to studies published in English, as the research team was proficient in this language.

IC3: Original Empirical Research: To ensure the reliability of findings, only studies based on original empirical research, including qualitative and quantitative approaches, were considered for inclusion.

IC4: Peer-Reviewed Publications: The review focused solely on peer-reviewed publications — journal articles while excluding dissertations and preprint papers.

IC5: Time Frame: The search was confined to articles published between 2013 and 2023 (before August) to capture the period coinciding with the widespread adoption and growth of algorithmic trading and financial artificial intelligence technology.

IC6: Quality Criteria: In adherence to scientific rigor, quality criteria were applied to exclude studies published in predatory journals, ensuring the credibility and validity of the selected sources.

The exclusion criteria are basically the counter side of the inclusion criteria. To intuitively present all the criteria, all our inclusion and exclusion criteria are shown in Table 1.

2. THE COORDINATE SYSTEM AND FOUR-QUADRANT THEORY OF MODERN FINANCIAL TRADING TECHNOLOGY

The financial landscape has been continually reshaped by technological advancements, propelling trading strategies to new levels of sophistication. As algorithmic trading, artificial intelligence, and machine learning have gained prominence, it has become evident that a comprehensive framework is necessary to understand the dynamic interplay between technology and trading strategy.

To conduct in-depth research on the progress of financial trading technology, we raise two important non-performance characteristics in empirical research on financial trading, namely: Machine technology and Trading Strategy. Machine technology represents the advanced level and complexity of machine technology in financial trading technology. Trading Strategy represents the advanced level and complexity of trading strategies in financial trading technology.

To fulfill this methodology, during the review study process, we evaluated the level of Machine technology and Trading Strategy for each empirical study of more than 100 articles in the database and manually assigned a score from 1 to 4.

The score of Machine technology level is calculated based on the following factors:

1. Technology type (for example DL, RL, DRL, and other models), advancement, and innovation;
2. Model automation and self-upgrading process;
3. Algorithm complexity (computing power required);
4. Others (advanced models and theories from other academic fields).

Here, we rate the traditional econometrical models and algorithm trading technologies rate at 2 points (such as ARIMA, technical indicators, and Monte-Carlo simulation) and rate the advanced 2-point models and classic models of ML and DL (SVM, RF, CNN, DNN, RNN) at 3 points. The improved ML/DL models and new models (such as RL, DRL, and advanced models from other subjects) are rated 4 points.

The score of the Trading Strategy level is calculated based on the following factors:

1. Type, advancement and innovation of strategies;
2. Financial factors considered in the strategy;
3. Multi-environment adaptability of strategies;
4. Others (introduction of theories in non-financial fields).

Here, we score 2 points for trading strategies that use model prediction as the main means to make profits, and 3 points for automated trading strategies and portfolio strategies that are executed as a whole. We rated the more advanced, with higher adaptability to multiple situations, and considered more dimensional parameters as 4 points. In addition, it should be noted that both

Machine technology level and Machine technology level have no direct relationship with trading performance in empirical research on financial trading, and only reflect the technological level of financial trading.

Then we counted all the scores of 130 academic articles on Machine technology and Trading Strategy under the coordinate system of Fig. 1 and obtained four quadrants with different characteristics: Quadrant I: high machine technology level, high trading strategy level. Quadrant II: low machine technology level, high trading strategy level Quadrant III: Low machine technology level, Low trading strategy level and Quadrant IV: high machine technology level, low trading strategy level. Under this system, each quadrant represents a unique intersection of these two crucial dimensions. Each represents a unique type of financial trading technology.

In subsequent research, we evaluated and summarized the financial trading technology in the selected articles, and in-depth summarized the characteristics and main performance of the four-quadrant financial trading technology. The Coordinate System and Four-Quadrant Theory of Modern Financial Trading Technology is a conceptual framework that seeks to provide a comprehensive understanding of the complex interplay between machine technology and trading strategies in the financial trading area.

Using of the abovementioned methods let us to get the following results.

1. Articles Review. By following the PRISMA 2020 standard, the initial search yielded 2,351 potentially relevant articles published between 2013 and 2023 (before August) and underwent further screening based on the relevance of their titles and abstracts. Subsequently, 522 articles were initially considered for eligibility after a rigorous examination of the updated search codes. Codes are as follows [26]:

TITLE-ABS (financial AND market AND trading AND (algorithm OR model OR prediction OR forecasting AND NOT effect AND NOT phenomenon AND NOT carbon AND NOT behavior)) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE , “p”) OR LIMIT-TO (SRCTYPE , “j”)) AND (LIMIT-TO (OA , “all”)) AND (LIMIT-TO (DOCTYPE , “ar”)) AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (PUBSTAGE , “final”))

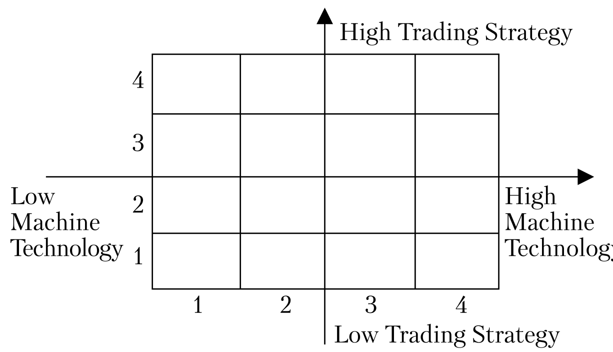

Fig. 1. The coordinate system and four-quadrant of modern financial trading technology
Source: generalization by the authors.

To ensure methodological integrity, the full texts of these 522 articles were thoroughly assessed for relevance, resulting in 130 articles (Annex 1) that met the inclusion criteria and were ultimately selected for the final review. As a result, by adhering to the PRISMA model, this systematic review guarantees a robust and unbiased analysis of technological advancements in financial trading. The 130 selected articles provide valuable insights into algorithmic trading, financial artificial intelligence, and other emerging technologies that have significantly impacted financial markets over the years.

Figure 2 shows the publication year distribution of the 130 selected articles. There is an obvious fluctuating increase trend in the publication number from 2013 to 2022. The reason is due to the widespread adoption and rapid growth of algorithmic trading technology and financial artificial intelligence from 2013 to 2022. Whereas, the publication amount has a sharp decrease in 2020. The reason may be caused by the global shock of COVID-19 in the scientific research field. Figure 2

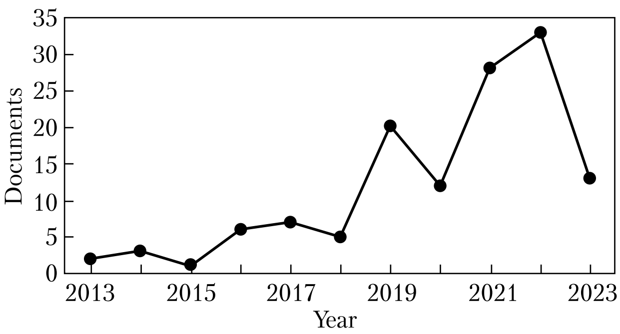

Fig. 2. Number of publications about financial trading technology by year during 2013—2023

Source: authors' selection from Annex 1.

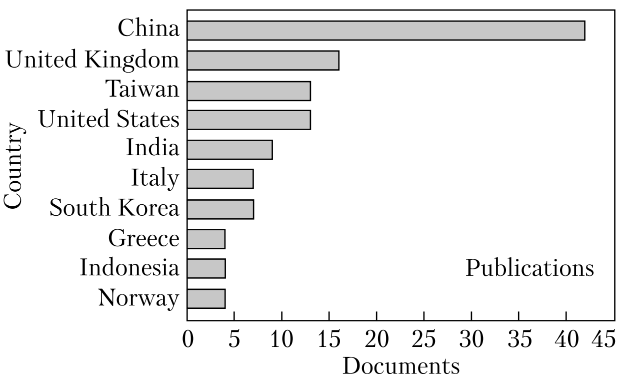

Fig. 3. Number of publications about financial trading technology by country or territory during 2013—2023

Source: authors' selection in Annex 1.

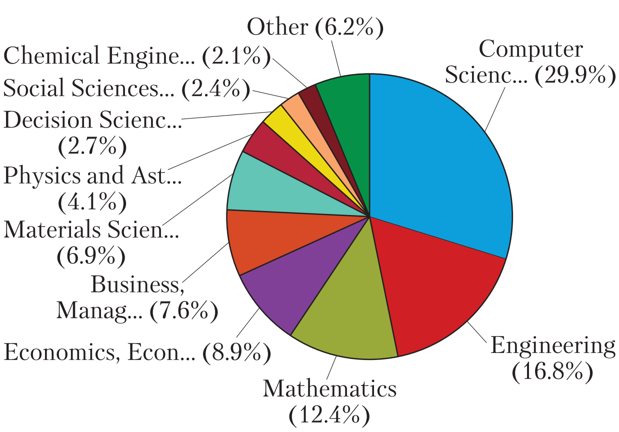

Fig. 4. Number of publications about financial trading technology by area during 2013—2023

Source: authors' selection in Annex 1.

also shows the huge scientific research potential of financial trading science publishing, and this topic may remain long-term scientific popularity in the future.

Then, Fig. 3 shows the main publication country/territory of the 130 selected articles. China is in the first rank in this chart, which has a total of 55 publications between 2013 and 2023 (including Taiwan and Mainland China). This is closely related to the rapid development of the Chinese financial trading market in the past decade, a large number of Chinese scholars have poured into the field of financial trading technology research. Besides, the UK and the USA also have over 10 publications between 2013 and 2023 respectively.

Furthermore, Fig. 4 shows the main subject area of the 130 selected articles, which is mostly according to their scientific publisher and academic classification. We can see the high percentages of Computer Science, Engineering, Mathematics, Economics/Econometrics/Finance, Business/Management/Accounting, Material Science and Physics. This shows that financial trading technology is a highly interdisciplinary research topic. The integration of multiple disciplines at the same time also provides a steady stream of research output for financial trading research.

In order to further fully understand the characteristics of the selected 130 research articles, Annex 1 shows the main categories of information, which are author, source, year, citations, technology applied, benchmark technology and main results. As a systematic review of technology, we applied two technological factors as categories: technology applied and benchmark technology. Technology applied refers to the types of the main financial trading technology applied during the research, which includes both financial trading strategies and machine learning models. Benchmark technology refers to the compared financial trading technology during the empirical financial trading application research as a benchmark of trading performance. Benchmark technology can be not only basic financial trading strategies like buy & hold strategy, but also other machine learning models which are compared under the same trading strategy.

The result of this systematic review shows financial markets have undergone significant transformations over the last decade with the help of rapid advancements in computer science and machine learning. Algorithmic trading, machine learning, and deep learning have emerged as key technologies driving innovation in financial trading strategies and financial market efficiency. By studying the selected 130 scientific articles, we summarized the traits and financial effects of each financial trading technology in detail. There are:

1. Algorithmic Trading:

Algorithmic trading involves the use of computer algorithms to execute trading orders with high speed and accuracy. Key traits of algorithmic trading include:

Speed: Algorithms execute trades at millisecond speeds, capitalizing on market inefficiencies.

Automation: Reduces human intervention, minimizing emotional biases and enhancing consistency.

Scalability: Algorithms can handle large volumes of trades simultaneously.

With financial effects improvements:

Efficiency: Algorithmic trading has led to increased market liquidity and price efficiency.

Arbitrage Opportunities: Algorithms exploit price discrepancies across markets, leading to more efficient price convergence.

Reduced Impact: Algorithms execute trades with minimal market impact, reducing transaction costs.

2. Machine Learning:

Machine learning involves the development of models that can learn from data and improve their performance over time. Traits of machine learning in finance include:

Prediction: Models analyze historical data to predict future price movements or market trends.

Adaptability: Machine learning models can adapt to changing market conditions.

Feature Extraction: Algorithms automatically extract relevant features from complex datasets.

With financial effects improvements:

Enhanced Predictions: Machine learning models improve trading strategies by providing more accurate predictions.

Risk Management: Models assess portfolio risks and recommend optimal risk management strategies.

Personalization: Machine learning tailors investment strategies to individual investor preferences.

3. Deep Learning:

Deep learning is a subset of machine learning that utilizes artificial neural networks to model complex patterns. Key traits include:

Complex Patterns: Deep learning models can capture intricate non-linear relationships in data.

Unsupervised Learning: Deep learning can perform unsupervised tasks like anomaly detection.

With financial effects improvements:

Pattern Recognition: Deep learning identifies subtle patterns that may be imperceptible to traditional methods.

Automated Feature Learning: Deep learning automatically learns relevant features from raw data, reducing the need for manual feature engineering.

Risk Assessment: Deep learning models assist in risk assessment by detecting anomalies in trading behavior.

In addition, during the systematic review research, we found several prominent themes and key findings, contributing to a deeper understanding of the evolving field of financial trading technology:

1. Innovations: We focus on the significant advancements in algorithmic trading strategies and machine learning technology. The articles show the researchers explored various machine learning techniques, neural networks, deep learning models, and reinforcement learning algorithms, demonstrating their application in financial trading to enhance efficiency and accuracy. At the same time, Financial trading technology innovation has the following characteristics:

- Financial trading technology innovation is closely integrated with the development of IT technology. From algorithmic trading to AI trading, financial transaction technology innovation can apply IT technology in a short period of time.

- In the recent decade, the speed of financial trading technology innovation has also accelerated. The reason is highly related to the development speed of ML algorithms has become faster, which is reflected in the new ML algorithm theory and the substantial increase in computer computing power.
- New technological innovations do not occupy a dominant position in the financial market, and traditional transaction analysis methods are still active in the market.

2. Predictive Analytics and Forecasting: Many studies focused on the integration of predictive analytics and forecasting methods in financial trading. By leveraging sophisticated algorithms, traders were able to make data-driven predictions, analyze market trends, and anticipate price movements, thereby gaining a competitive edge in the financial markets.

3. Risk Management and Mitigation: Financial trading technology has revolutionized risk management practices, with the help of advanced risk assessment models and real-time monitoring systems that have been employed to mitigate potential financial risks and ensure robust risk management protocols. Furthermore, the enhancement of the complexity-handling ability of machine learning modes enables the recognition of intricate market patterns and behaviors.

4. Automated Trading Systems: The systematic review shows the prevalence and impact of automated trading systems. These systems execute trades based on predefined algorithms, minimizing human intervention and responding rapidly to market changes, thus increasing the speed and efficiency of trading.

5. Big Data and Market Analysis: Researchers explored the role of big data in financial trading and its effect on market analysis. This review demonstrates how vast amounts of data are processed and analyzed to gain insights into market behavior and identify profitable trading opportunities.

2. The Coordinate System Four-Quadrant of Modern Financial Trading Technology. During the systematic review study, we scored all the articles based on the scoring basis of machine technology and trading strategy. Figure 5 shows the number of papers for each score of machine technology and trading strategy. Because of the high level and advanced nature of the selected article database, neither machine technology nor trading strategy has a score of 1. Regarding the scores of machine technology, 33 articles scored 2 points, 46 articles scored 3 points, and 51 articles scored 4 points. On the other hand, the scores of trading strategy were 78 articles with a score of 2, 37 articles with a score of 3, and 15 articles with a score of 4. There are a lot of articles with a score of 2 for trading strategy and a score of 3—4 for machine technology, accounting for nearly half of all articles. At the same time, the different number of articles and numerical distribution in the matrix intuitively reflect the technical level and scientific research quality of financial transaction research to a certain extent.

After analyzing and summarizing the financial trading technology in the selected articles, we built the Coordinate System and a Four-Quadrant of financial trading technology development which maps machine technology on the abscissa axis and trading strategy on the ordinate axis. And delineates four distinct quadrants, each representing a unique intersection of these two crucial dimensions. Figure 6 shows the Four-Quadrant theory divides the technology-trading strategy space into four distinct quadrants.

The framework of the Four-Quadrant theory is as follows:

1. Quadrant I: Autonomous intelligent trading (high machine technology level, high trading strategy level).

This quadrant represents the future development trend of financial trading technology. The autonomous intelligent trading system has powerful machine learning and deep learning capabilities, and can independently formulate complex trading strategies, adapt to market changes and continuously optimize strategies.

Autonomous intelligent trading, as the trading method with the highest level of technology and strategy in the Four-Quadrant theory, its researches and applications usually have the highest difficulties and complexity. As an example, a study in our article database (No. 67 from Annex 1) has introduced a novel decision support system for automated stock trading based on deep reinforcement learning that observes both past and future trends of stock prices whether single and multi-step ahead as an observing state to make the optimal trading decisions of buying, selling, and holding the stocks [27].

2. Quadrant II: Intelligent assisted trading (low machine technology level, high trading strategy level).

In this quadrant, artificial intelligence is used to assist human trading decisions. Through the analysis of large amounts of historical data, AI can provide insights and recommendations, but trading strategies are still dominated by traders. The researchers of Intelligent assisted trading are usually financial research and application experts in the field, and often use advanced financial quantitative trading strategies in their research.

3. Quadrant III: Traditional modern trading (Low machine technology level, Low trading strategy level).

In this quadrant, trading also takes use of the advantages of machine learning technology. Traders make decisions based on their experience and market insight, and the application of technology is relatively limited. Methods such as traditional stock and futures trading dominate this quadrant.

Traditional modern trading on the one hand includes fundamental analysis and technical analysis, and on the other hand, it also includes the application of primary machine learning tools, such as regression models, time series analysis, etc. Algorithmic trading has grown rapidly inspired by the help of these tools. Whereas, now this type of new research has also declined, and at the technological level Traditional modern trading research is gradually being replaced by a large number of Mechanical trading research institutes.

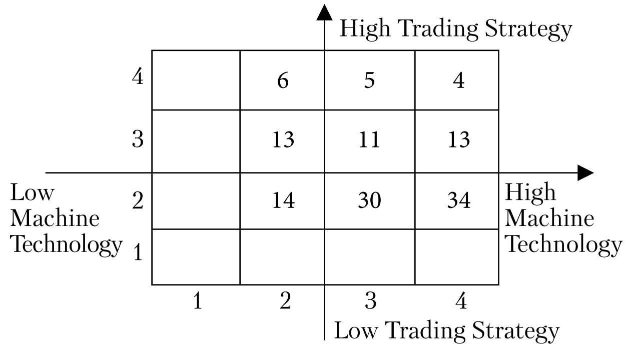

Fig. 5. Matrix of the number of papers for each score
Source: authors' generalization.

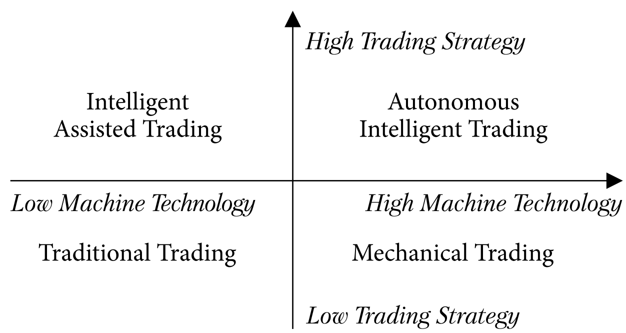

Fig. 6. Four-quadrant of modern financial trading technology
Source: created by the authors.

4. Quadrant IV: Mechanical trading (high machine technology level, low trading strategy level).

Mechanical trading uses preset rules and algorithms to automatically execute transactions, reducing the interference of human factors. This trading method emphasizes technical analysis and the use of market signals, but the trading strategy is relatively simple and cannot fully cope with the complexity of the market.

Mechanical trading usually relies on forecasting and executing simple financial trading schemes. In our article database, more than half of the research types are more biased toward Mechanical trading, and they rely on simple forecasting strategies to make financial trading through advanced ML/AI applications. As an interdisciplinary technology, financial transaction technology has received contributions from mathematics, physics, computer and engineering scholars on the one hand, and has attracted extensive attention from these not-finance scholars on the other hand.

A large number of financial transaction research based on not-finance theory emerged in 2013—2023. In addition to most of the research on various ML/AI forecasting models, there is also some transfer research based on theories of other scientific disciplines. As an example, a study in our article database (No. 28 from Annex 1) builds a prediction model in trading in the financial Forex market. The prediction model is based on the deviations from the closed string/pattern form (PMBCS), which is from the string theory in Physics [28].

The Four-Quadrant Theory provides a comprehensive framework for analyzing the intersection of machine technology and trading strategy. By categorizing interactions into four distinct quadrants, this theory enhances our understanding of the complex financial trading technology applications. It highlights the diversity of interactions within this space and emphasizes the role of human expertise in harnessing the potential of technology. With the continuous evolution of technology and financial markets, trading technology will innovate in different quadrants, bringing new opportunities and challenges to the future of financial markets. Through further exploring of the four-quadrant theory, the development of financial trading technology will be more intelligent and diversified, and data-driven decision-making and powerful artificial intelligence systems may become the core of transactions. In addition, the theory is also conducive to scientific research on the relationship between financial trading technical level and trading performance.

The findings from this systematic review have significant implications for the future of research and practice in financial trading technology, at the same time, it reflected in the following aspects which need to be discussed further:

1. Data Quality and Ethical Considerations: Accurate and clean data is essential for the success of these technologies. Similarly, as financial trading technology becomes more sophisticated, researchers and practitioners must require of science ethics related to algorithmic decision-making, fairness and research transparency.

2. Overfitting: Models may perform well on historical data but fail in live trading due to overfitting. The overfitting problem often occurs in the backtesting phase of financial trading models, and the backtesting results without applicability make the model unprofitable in real-world trading. This is a critical technical issue in the financial trading technology area, and we will focus on this issue in subsequent research.

3. Market Regulation and Oversight: Policymakers and regulatory bodies should continuously review and update existing regulations to keep pace with the evolving landscape of financial trading technology and ensure market stability and investor protection.

In conclusion, this systematic review offers valuable insights into the technological advancements in financial trading, encompassing algorithmic trading, machine learning, predictive analytics, and other emerging technologies. The identified themes and implications provide a foundation for further research and practical applications, contributing to the continued growth and development of financial markets in an increasingly technologically driven landscape. Furthermore, we innovatively propose a Four-Quadrant theory of modern financial trading technology based on 2 dimensions' total of 8 factors. The theory offers a structured approach to understanding the interaction between machine technology and trading strategies, by dividing these interactions into four quadrants. As both technology and financial markets evolve, innovations within each quadrant will shape new opportunities and challenges for the future of trading. At the same time, it emphasizes the importance of human expertise in leveraging technological advancements. For directions of future studies, the following may need to be paid special attention:

1. Hybrid Technology and Continued Technological Advancements: The combining of algorithmic, machine learning and deep learning tech-

niques for synergistic benefits shows a good practice performance. Besides, future research should focus on exploring and evaluating the potential of emerging technologies, such as large language model (LLM), quantum computing and blockchain to improve trading efficiency, risk management, and adaptability to market conditions.

2. Application of the Four-Quadrant Theory: The proposed Four-Quadrant Theory provides a framework for categorizing financial trading technologies based on machine technology and trading strategies. Future research should continue to expand on this theory, exploring each quadrant's potential in real-world applications, particularly focusing on Quadrant I (high machine technology, high trading strategy) as it represents the cutting-edge development of autonomous intelligent trading systems.

3. Scientific Assessment of Financial Trading Technology Performance: It is crucial to establish a more standardized and scientific approach to assessing the performance of financial trading technologies. Future research should include in-depth empirical studies that evaluate these technologies across different market conditions, strategies, and performance metrics. This assessment should include not only profitability but also factors like risk exposure, adaptability, and the scalability of technologies.

These directions should help guide the next wave of scientific inquiry into the evolving landscape of financial trading technologies.

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ТЕХНОЛОГІЧНІ ДОСЯГНЕННЯ У ФІНАНСОВОМУ ТРЕЙДИНГУ: СИСТЕМАТИЧНИЙ ОГЛЯД ЛІТЕРАТУРИ

Вступ. Трансформаційні перетворення кардинально змінили фінансові ринки, що зумовлює необхідність переоцінювання поточних знань і майбутніх тенденцій використання технологій у фінансовому трейдингу.

Проблематика. Використання різноманіття технологічних досягнень у фінансовому трейдингу вимагає їх структуризації залежно від рівня машинної технології та рівня торгової стратегії.

Мета. Всебічне узагальнення наявних джерел про технологічні досягнення у фінансовому трейдингу для оцінювання якості наукових досліджень і окреслення перспективних напрямків подальших розробок.

Матеріали й методи. Аналітичне вивчення літературних джерел щодо технологічних досягнень у фінансовому трейдингу здійснено відповідно до стандарту *PRISMA* 2020. Взято до дослідження 130 наукових статей (за період 2013—2023 рр.) про технології фінансового трейдингу. Інноваційну теорію чотирьох квадрантів було використано для аналізу синергії між машинними технологіями та торговими стратегіями, що базується на 8 факторах у двох вимірах.

Результати. Ключові фінансові технології охоплюють алгоритмічну торгівлю, машинне навчання та глибоке навчання. Кожен з цих складників має унікальні властивості: швидкість, автоматизація, адаптивність і розпізнавання складних шаблонів. Ці технології покращили ефективність ринку, управління ризиками та персоналізовані торгові стратегії. Теорія чотирьох квадрантів пропонує структурований підхід до розуміння взаємодії між машинними технологіями та торговими стратегіями і поділяє взаємодії на чотири квадранти.

Висновки. Інноваційне застосування теорії чотирьох квадрантів дозволяє припустити, що подальше дослідження може призвести до більш розумних, диверсифікованих торгових систем, де прийняття рішень на основі даних і штучного інтелекту відіграють ключову роль. Гібридні технології, наукова оцінка продуктивності та передові розробки автономних інтелектуальних торгових систем є важливими для подальшого вивчення технологій фінансового трейдингу.

Ключові слова: управління ризиками, фінансовий ринок, фінансові технології, штучний інтелект, алгоритмічна торгівля, машинне навчання, глибоке навчання.