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Artificial intelligence techniques in financial trading: A systematic literature review

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ABSTRACT

Artificial Intelligence (AI) approaches have been increasingly used in financial markets as technology advances. In this research paper, we conduct a Systematic Literature Review (SLR) that studies financial trading approaches through AI techniques. It reviews 143 research articles that implemented AI techniques in financial trading markets. Accordingly, it presents several findings and observations after reviewing the papers from the following perspectives: the financial trading market and the asset type, the trading analysis type considered along with the AI technique, and the AI techniques utilized in the trading market, the estimation and performance metrics of the proposed models. The selected research articles were published between 2015 and 2023, and this review addresses four RQs. After analyzing the selected research articles, we observed 8 financial markets used in building predictive models. Moreover, we found that technical analysis is more adopted compared to fundamental analysis. Furthermore, 16% of the selected research articles entirely automate the trading process. In addition, we identified 40 different AI techniques that are used as standalone and hybrid models. Among these techniques, deep learning techniques are the most frequently used in financial trading markets. Building prediction models for financial markets using AI is a promising field of research, and academics have already deployed several machine learning models. As a result of this evaluation, we provide recommendations and guidance to researchers.

1. Introduction

Due to their non-linear, non-stationary, and time-variant nature, financial markets can be considered a complex system. They are also sensitive and vulnerable to various variables, such as economic news, political events, and international influence (Leles et al., 2019). With technology breakthroughs and improvements, Artificial Intelligence (AI) approaches have become widely used in financial markets, altering how financial transactions are handled and improving financial services' efficiency, security, and personalization. A new horizon in finance is represented by financial technology, or FinTech, which uses technology to innovate and answer long-standing market problems in addition to automated trading, investments, insurance, and risk management (Gai et al., 2018).

AI has proven beneficial in the financial sector in areas such as process automation, risk management, and customer service development. Personalized customer experiences can be achieved through advanced analytics and natural language processing, automated repetitive tasks, and risk assessment and reduction by analyzing large datasets with AI algorithms. AI is also used in the banking industry, where it powers offer personalization, improves fraud protection measures, and democratizes access to banking services, particularly in underprivileged areas. AI is revolutionizing the investment and insurance industries by facilitating automated risk management, tailored investment programs, and market forecasting (Ferreira et al., 2021).

Though there have been improvements, there are still difficulties in integrating AI in the financial markets. Significant challenges include data quality, ultra-high frequency data processing, and economic indices' noisy and dynamic character. Furthermore, because financial markets are multivariate, even minor adjustments to one element can significantly impact trading choices and results (Dang, 1121).

AI-enhanced algorithmic trading significantly impacts financial trading by mining critical data and providing inexpensive and easily accessible tools that benefit everyone, not just companies. AI investing

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judgments will be precise, reliable, and unbiased, unlike those made by more emotive humans. The next phase of trading algorithms will include AI, allowing them to learn from the trading records of thousands of previous experiences. This is accomplished through the use of machine learning algorithms that discover patterns in data and generate predictions. As a result, AI algorithmic trading offers several benefits and advantages over traditional human algorithmic trading (Ta et al., 2018; Li et al., 2020). For example, AI's ability to respond to market conditions, allowing it to predict based on sentiment, it can discover hidden patterns that humans cannot capture due to the massive amount of data, accuracy, speed, 24-hour nonstop operation, and most cost-efficiency all achievable with incredibly powerful computers and AI technology. Another significant advantage is the absence of human emotions. Because humans are often motivated by the fear of taking risks and losing, their actions might be influenced negatively by wrath, jealousy, or fear. On the other hand, AI algorithmic trading is based on statistical, confident conclusions created by examining past data and a wide range of market situations.

Even though AI is frequently used in financial markets, researchers encounter several challenges. One of the primary difficulties is data, which includes data quality, ultra-high frequency data processing, and rapidly adding new data sources such as social mainstream media and economic news. Furthermore, financial indices are extremely difficult to analyze due to their multivariate nature, noisiness, and dynamicity (Mourelatos et al., 2018). Another issue is algorithmic behavior, as financial markets include a few or dozens of variables; typically, a tiny change in a variable may have a devastating influence on performance; so, making a trading decision is a systematic operation that should take a lot of practical considerations into account (Deng et al., 2017).

In the financial trading industry, AI techniques have become vital tools that drive advancements and address ongoing problems with risk assessment, portfolio management, and market prediction. Despite the technology's quick development and application in the financial markets, there is still a substantial gap in systematic reviews of AI techniques in the trading markets. This gap emphasizes the need for a thorough investigation to comprehend the state of AI approaches and trading analysis tools for financial market trading. To the best of our knowledge, no previous study has systematically focused on AI techniques and applications in the trading market. As a result, we give a detailed systematic literature review in this study to better comprehend the research on using AI in financial trading markets. This study is an overview of research published between 2015 and 2023. Specifically, we focus on which AI approaches are commonly employed and which models exploit their strengths in anticipating asset price patterns to assist traders in taking the most profitable action. We hope this assessment will provide scholars with a better grasp of the present level of AI progress and use in trading markets, allowing them to identify holes that need filling and casting more light on.

The research was adequately carried out, and the articles chosen addressed the following concerns: (i) the financial trading market and the asset type, (ii) the trading analysis type considered along with the AI technique, and (iii) the AI techniques utilized in the trading market, (iv) the estimation and performance metrics of the proposed models.

The remainder of the paper is organized as follows: Section 2 introduces a background that covers the essential principles and fundamentals of trading. Section 3 is a review of the literature surveys. Following that, in Section 4, an outline of the research's approach technique is offered. Section 5 discusses the findings and outcomes of this review. Section 6 concludes with insights and recommendations for future research.

2. Background

This section presents a brief background information on the fundamentals of financial trading.

2.1. Japanese candlesticks

Several price charting approaches include line charts, bar charts, and candlestick charts. Candlestick charts are by far the most known and commonly utilized among them. These charts were established in Japan almost a century before the line and bar charts were invented in the West. While there was a relationship between price, supply, and demand for rice in the 1700 s, a Japanese man named Homma observed that merchants' emotions heavily impacted the markets (Northcott, 2009). The ability of candlesticks to demonstrate emotion by graphically displaying the volume of price changes with distinct colors makes them preferable. Therefore, candlestick charting allows traders to analyze the price behavior of the studied market.

A Japanese candlestick is a pattern that displays the whole price movement over a certain period. The primary two colors that define the price movement direction are green and red, with green candlesticks representing a bullish or upward price movement. The red candlestick, on the other hand, denotes a bearish or downward price trend. A candlestick's significant features are the body and shadow and four price aspects: the opening price, closing price, highest price, and lowest price. The body reflects the price range between the opening and closing for a certain period. If the closing price is lower than the opening price, the candle is bearish and generally filled with red or black. If, on the other hand, the closing price is more than the opening price, the candle is considered bullish and is generally filled with a green or unfilled body color. Fig. 1 illustrates the difference between a bearish and a bullish candlestick and represents the main components of a candle. As a result, the Japanese candlestick chart is made up of continuous candles that change depending on the time range, which might be 1 min, 5 min, 30 min, 1 h, and so on.

Traders frequently utilize the primary cause of Japanese candlestick charts: evaluating and anticipating market price behavior. Therefore, various patterns may predict price movement accordingly. The longer the periods, the more precise the symbolism of the Japanese candles. Simultaneously, the ability to evaluate the forecast is improving. A five-minute candlestick chart, for example, will yield better results than a one-minute candlestick chart.

2.2. Trading analysis types

Traders employ many trading analyses to forecast market moves and evaluate patterns. Traders typically use one or a mix of these analysis techniques to suit their trading style. These categories are broadly classified as shown in Fig. 2 (Leles et al., 2019):

a) Fundamental analysis

The fundamental analysis approach consists of analyzing the impact of economic news that affects the market, using economic factors to estimate the intrinsic values of financial securities (Ta et al., 2018). It can be used to trade in this market.

A calendar is a handy tool in the market that maintains track of all the significant events and economic data that affect the market. It describes events and their relevance to global markets. These calendars assist traders in efficiently managing risk and place them in a position to plan forward.

b) Technical analysis

Technical analysis is based on statistical methods and charts that depict the price movement of a market over one year, with each point on the graph representing the closing price for each trading day. In the financial markets, technical analysts look for price patterns and market trends that they might exploit. This analysis aims to extract (non-linear) patterns that will be used to build trading strategies from the analysis of the price series of financial securities, capturing significant market

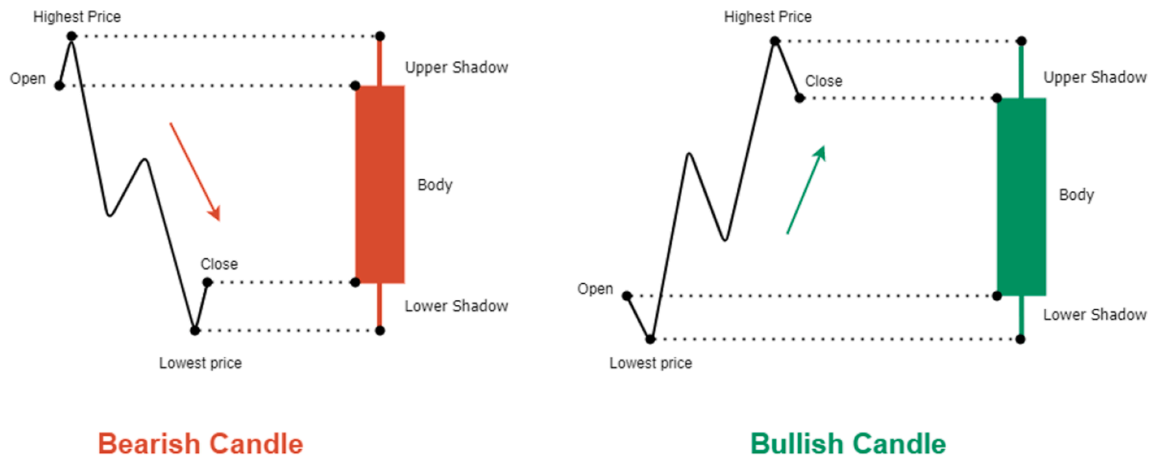

Fig. 1. The Difference Between a Bullish and a Bearish Candlesticks.

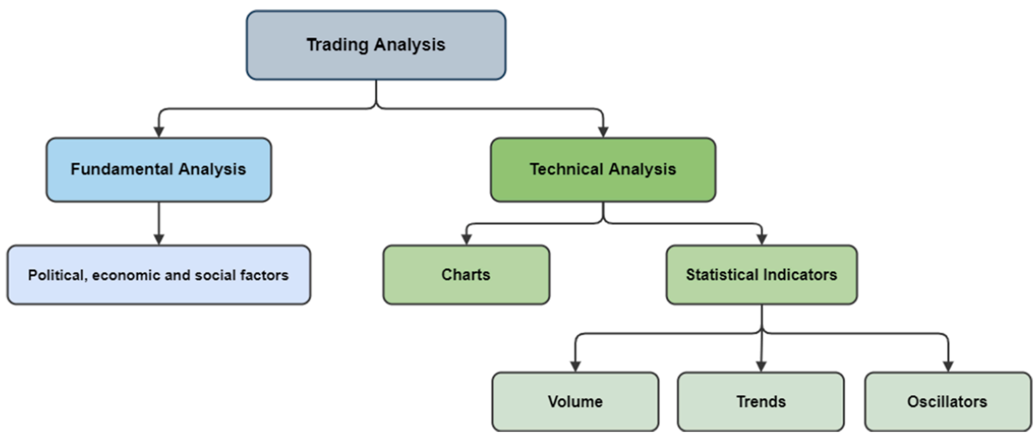

Fig. 2. Trading Analysis.

movements and ignoring their random fluctuations.

Table 1 compares the major types of analysis. The table indicates that technical analysis predicts price movement by employing price charts, statistical indicators (such as moving average, relative strength index, moving average convergence divergence, etc.), and oscillators. On the other hand, fundamental analysis is focused on economic analysis, which demands considerable investigation and the study of financial statements based on the sentiment of market-relevant news.

2.3. Algorithmic trading

Algorithmic trading is any trading that uses complex algorithms to automate the trading process. Algorithm trading is often characterized by learning, reasoning, and decision-making (Treleaven et al., 2013). With the improvement of computer computing capability, algorithmic trading has grown in popularity. Algorithmic trading attempts to use current computers' intensity and computing power compared to human brokers. They are noted for their rapid and accurate operations, which minimize trading costs and increase trade precision and variability (Mathur et al., 2021). Furthermore, the trader can use a process known as backtesting to analyze the performance of a strategy or model using historical data. Backtesting allows traders to fine-tune and enhance their models and tactics.

Algorithmic trading employs models that adhere to predetermined strategies. These models can include basic yet successful tactics such as creating a take profit and stop loss action depending on the current price and the prior day's range. Furthermore, the development of robust, complicated models has been possible with AI approaches. These models correspond to a methodology that has been carefully back-tested across various market circumstances. This corresponds to validating and testing a machine learning model to minimize overfitting and fine-tune its weights to achieve optimal parameters. Given this, backtesting is frequently continued by simulated trading using real-time data. If this continues to be effective, the algorithm will most likely be deployed to trade and constantly watched to assess its viability. If the performance deteriorates, the system will adapt and redeploy it, permitting developers to progressively update and optimize it until they achieve the ideal actions (Li and Peng, 2019).

Table 1
Comparison between Fundamental and Technical Analysis.

	Fundamental Analysis	Technical Analysis
Objective	Determining market value to determine if an asset is undervalued or overvalued	Determining the appropriate trading time to enter/buy or exit/sell in the market
Concept	Following the sentiment and concentrating on the market's economics	Using statistical indicators to investigate price behavior to forecast future price movement
Dependency	News, economy, and financial statements	Charts such as candle sticks. And use technical indicators.
Function	Trading and investment	Trading
Usage	Extensive investigation of historical and current data is required	Comprises information of historical data from the past.
Time Frame	Long-term trading	Short-term trading

3. Literature review

As the first step of the systematic review, survey articles focused on AI in financial trading were reviewed. Only survey articles that study AI in financial markets are Several surveys for AI in financial trading have been conducted. For instance, Li, Wu, and Bu (Li et al., 2016) present a pilot survey on using machine learning for quantitative trading. The authors tackled quantitative trading from several perspectives, including price trends, forecasting, and portfolio selections. In addition, they categorize the price prediction in the stock market using the following techniques: neural network, support vector machine, wavelet analysis, and text mining for learning portfolio selection.

Henrique, Soberiro, and Kimura (Henrique et al., 2019) provided a bibliographic analysis highlighting machine-learning approaches for forecasting financial market values. The authors analyzed 57 articles, and their findings revealed that the most commonly employed models in price forecasting are support vector machines and neural networks. According to the authors, this study issue is still important, and using data from developing markets provides a research opportunity.

Several studies and works have been done in the stock market. For example, Bustos and Pomares-Quimbaya (Bustos and Pomares-Quimbaya, 2020) thoroughly reviewed stock market trend prediction. The forecasting methodologies are classified, characterized, and compared from 2014 to 2018. Their study and analysis show that technical indicators are critical in projecting the market. Furthermore, ensemble models have highly predictive predictions. Surprisingly, they claim that deep learning models did not beat traditional methods, which might be attributed to a lack of datasets. Ferreira et al. (Ferreira et al., 2021) give another evaluation covering a wide range of works from 1995 to 2019 investigating AI in stock market trading. The authors classified AI applications in the stock market into four categories: portfolio optimization, stock market prediction using AI, financial sentiment analysis, and combinations of two or more methodologies. Another study by Kurani et al. (Kurani et al., 2023) focused on the stock market. However, the authors' study considers two popular machine-learning techniques: Artificial Neural Networks (ANN) and Support Vector Machine (SVM). Many other studies emphasize the stock market and AI, such as the following (Le et al., 2020; Chopra and Sharma, Nov. 2021).

Another part of the survey used deep learning and deep reinforcement learning techniques in trading. Millea, for example, (Millea, 2021) presented a brief overview of DRL applications in cryptocurrency markets. According to the author, the most generally used model is the convolutional neural network, and the Sharpe ratio is often employed as a performance metric. Li and Bastos (Li and Bastos, 2020), on the other hand, did a thorough literature review on deep learning and technical analysis in the stock market. Their systematic study focuses on four areas: price forecasting approach, trading strategy, profit evaluation and measures, and risk management. According to their findings, the LSTM approach is the most often employed. Deep Learning has quickly emerged as a potent technique for modeling and forecasting unpredictable financial markets worldwide, especially in the stock market. Focusing on the European Union stock market, the authors Ketsetsis et al. (Ketsetsis, et al., 2020) presented a systematic review analyzing the deep learning techniques in the European stock market.

FinTech, or the intersection of finance and technology, transforms traditional financial services with new digital solutions that improve accessibility, efficiency, and inclusion. FinTech's fast growth continues to change how consumers and organizations handle their financial transactions and investments, from mobile payments to robot advisors. Ashta and Herrmann (Ashta and Herrmann, 2021) present a review that discusses the opportunities and risks of using AI in the financial sector, including banking, investments, and microfinance. It provides an overview of how AI transforms the financial industry and what financial organizations must consider when integrating this technology. On the other side, Bayramoğlu (Bayramoğlu, 2021) examined the application areas of AI in both FinTech and RegTech, which refers to regulatory technologies. The author discusses AI's impact on Fintech and its benefits for regulatory authorities. In addition, the paper highlights the risks associated with Fintech and how RegTech can help to regulate Fintech without harming its positive potential. Overall, the paper provides insights into the exciting world of AI in FinTech and RegTech and how it is revolutionizing financial services.

Several studies focused on finance as a main huge domain and how AI and machine learning are affecting it from several factors. In (Milana and Ashta, 2021), the authors of this literature review on the application of AI in finance and financial markets present insights into the industry's prospective benefits and obstacles. They examine various research and approaches, including fuzzy set qualitative comparison analysis and abductive learning networks, to assess the influence of AI on market value added, risk management, and long-term growth. They also examine the frequency distribution of articles on AI in finance over time, revealing a recent surge in interest—another study presented by Aziz et al. (Aziz et al., 2022). The authors of this study employ a data science topic modeling technique to create a thorough and trend-based knowledge of the structure of research in machine learning and finance. They find 15 consistent study themes and categorize them into four groups while also recognizing the limits of their technique. On the other hand, the authors in (Chen et al., 2022) explore the cross-disciplinary field of financial engineering and how it has successfully integrated various quantitative analysis disciplines, including deep learning. Several research studies, such as those reported by Gogas and Papadimitriou (Gogas and Papadimitriou, 2021), examine the practical uses of machine learning in economics and finance. They describe how recent improvements in ML architectures have enabled the employment of ML techniques in fields where data sets are intrinsically small, such as macroeconomics or microeconomics applications. The authors also emphasize the novel and inventive uses of machine learning algorithms that bring fresh and substantial empirical insights into economics. Their work comprises 17 studies ranging from predicting economic and financial factors to modeling a whole stock market. Additionally, Pallathadka et al. (Pallathadka et al., 2023) provide an overview of the applications of AI in e-commerce and finance. Their study highlights how AI is being used to improve customer experience, supply chain management, operational efficiency, and product quality control. The study also discusses the differences between machine learning and deep learning, two of the most commonly used AI approaches.

Two research focused on delivering a review of bibliometric analysis. To begin, Goodell et al. (Goodell et al., 2021) undertook a bibliometric evaluation of AI and Machine Learning research in finance. They sought to determine the conceptual formation of AI and ML in finance research by evaluating the bibliometric structure of publications, journals, authors, organizations, and nations. The authors used a four-step approach for bibliometric reviews, which included establishing the objectives and scope of the evaluation, selecting the techniques for analysis, gathering data for analysis, conducting the analysis, and reporting the findings. The report thoroughly examines the research on AI and machine learning in finance, highlighting major themes and research clusters. Conversely, Ahmad et al. (Ahmed et al., 2022) offered another bibliometric evaluation of the literature on applying AI and machine learning in finance. They used bibliometric and scientometric methodologies to examine literature's most critical scientific actors, including documents, authors, journals, institutions, and countries. The authors conducted keyword co-occurrence, factorial analysis, trend analysis, co-authorships, and bibliographical coupling using VOSviewer and RStudio. The research thoroughly examines the literature on this topic, identifying the most active countries, groups, sources, documents, and writers.

Table 2 summarizes the surveys discovered, the number of articles analyzed, the overall number of citations, the period of articles covered, the financial market covered, and the prediction approach used. In addition, we present Table 3, which provides a comprehensive summary

Table 2
Overview of Related Work.

Ref.	Year	Survey Type	Range of Selected Studies	Financial Domain	Prediction Technique
(Li et al., Aug. 2016)	2016	Pilot survey	1988–2014	Financial trading market	Machine learning
(Henrique et al., Jun. 2019)	2019	Literature review	1991–2017	Financial trading market	Machine learning
(Bustos and Pomares-Quimbaya, 2020)	2020	Systematic survey	2014–2018	Stock market	Machine learning
(Li and Bastos, 2020)	2020	Systematic survey	2017–2020	Stock market	Deep learning
(Ketsetsis, et al., 2020)	2020	Systematic survey	2011–2019	Stock market	Deep learning
(Le et al., Nov. 2020)	2020	Comprehensive review	2018–2020	Stock market	Machine learning and deep learning
(Millea, 2021)	2021	Critical survey	–	Financial trading market	Deep reinforcement learning
(Ferreira et al., 2021)	2021	Review	1995–2019	Stock market	AI
(Kumar et al., Jan. 2022)	2021	Systematic survey	2002–2019	Stock market	Machine learning
(Ashta and Herrmann, May 2021)	2021	Overview	2008–2019	Fintech, banking, investment	AI
(Goodell et al., 2021)	2021	Bibliometric review	1986–2021	Finance	Machine learning
(Milana and Ashta, 2021)	2021	Overview	1985–2021	Finance, Finance market	AI
(Gogas and Papadimitriou, 2021)	2021	Overview	1974–2022	Finance, e-commerce	Machine learning
(Bayramoğlu, 2021)	2021	Overview	2002–2016	FinTech, RegTech	AI
(Chopra and Sharma, Nov. 2021)	2021	Systematic survey with bibliometric analysis	1993–2019	Stock market	AI
(Ahmed et al., Oct. 2022)	2022	Bibliometric review	2011–2021	Finance	Machine learning
(Aziz et al., Jun. 2022)	2022	Topic modeling approach	1990–2020	Finance	Machine learning
(Chen et al., 2022)	2022	Overview	2020–2022	Financial engineering	Deep learning
(Kurani et al., 2023)	2023	Comprehensive comparative Study	1970–2020	Stock market	Artificial neural network, Support vector machine
(Pallathadka et al., Jan. 2023)	2023	Overview	2013–2021	finance, business, e-commerce	AI
Ours		**Systematic literature review**	**2015–2023**	**financial trading market**	**AI**

of the surveyed literature.

Our Systematic Literature Review (SLR) on applying AI in financial trading distinguishes itself from existing state-of-the-art reviews through several vital aspects, underscoring our unique contributions to academic and practical understanding of this dynamically evolving field.

1) **Wide-ranging and Comprehensive:** Unlike previous surveys that might concentrate on particular financial markets (like stocks, cryptocurrencies, or foreign exchange) or AI methods (such as solely deep learning), our SLR covers a broad range of AI techniques, including machine learning, deep learning, and reinforcement learning, used across a variety of financial trading markets. Because of this inclusive approach, our review can provide a more thorough overview of AI's application in financial trading, emphasizing cutting-edge applications and interdisciplinary developments.
2) **Clarity of Basis and Concepts:** We start by explaining the fundamental ideas and techniques of financial trading, such as candlestick charting and different approaches to trade analysis. A condensed explanation of the concepts of algorithmic trading follows this. Our SLR stands out by guaranteeing accessibility and comprehensiveness, providing readers with a solid theoretical foundation to fully understand the subsequent exploration of AI in trading markets.
3) **Thorough Analysis and Data Collection**: We have carefully examined 143 publications from 2015 to 2023, extracting meaningful information in several areas, including the financial trading market, the kinds of assets traded, the AI models and approaches employed, the types of trading analyses, system features and outputs, datasets and their sources, metrics for evaluating model performance, publication types, and the distribution of papers over time. This precise data collection process enables us to create an in-depth overview of state-of-the-art AI applications in financial trading by identifying patterns, standard procedures, and noteworthy results.
4) **Identifying Gaps and Future Recommendations:** Besides synthesizing existing knowledge, our systematic examination identifies essential research gaps and suggests directions for future study. In this way, our SLR guides future research, encouraging ideas and investigation in underrepresented fields within the AI and financial trading intersection.

The purpose of our article is to review AI techniques used in financial trading in a systematic approach. We conducted a thorough analysis of published research from 2015 to 2023 to determine the most popular AI techniques and how they make the most of their advantages in predicting asset price patterns to help traders make better decisions. The primary message we wanted to get across was that by identifying the state-of-the-art AI applications used in financial trading markets, we could highlight common approaches, instruments, and results. This collected data aided in identifying study patterns in the usage of AI in trading during the last decade. The data collected during our study shed light on gaps in the literature and recommendations, including the future direction of research in this field. This will ideally aid future scientists in discovering new study subjects in this field and finding viable solutions to fill gaps and flaws in the present research.

4. Methodology

The survey in this paper is based on Kitchenham and Charters' Systematic Literature Review (SLR) approach (Kitchenham, 2007). It comprises three phases: planning, conducting, and reporting, each containing several stages. During the planning phase, we provide a review methodology that includes six stages: defining research objectives, developing a search strategy, identifying study selection processes, establishing quality evaluation guidelines, laying out the data extraction technique, and synthesizing the collected data. The stages are illustrated in Fig. 3.

We established our goals and built our research questions around them to narrow down our research questions. The search strategy is described as selecting proper search phrases that, when utilized, will lead to the discovery of relevant articles for our inquiry. The research technique used in this study is depicted in Fig. 4.

Table 3
Summary of Related Work.

Ref.	Summary
(Li et al., Aug. 2016)	An initial machine learning survey for quantitative trading. Addresses portfolio selection, price, and trend prediction. Include methods such as text mining, neural networks, SVM, and wavelet analysis.
(Henrique et al., Jun. 2019)	A review of the literature on machine learning for financial market predictions. SVM and neural network methods were highlighted in the analysis of 57 articles. It finds research opportunities in data from developing markets.
(Bustos and Pomares-Quimbaya, 2020)	A review of techniques for predicting stock market trends. Their emphasis is on ensemble models and technical indicators.
(Li and Bastos, 2020)	A Review of the literature on technical analysis and deep learning in the stock market. They emphasize risk management, trading strategy, profit assessment, and price forecasting. Additionally, LSTM was found to be the most popular method.
(Ketsetsis, et al., 2020)	This review systematically analyzes deep learning in the European stock market and emphasizes its effectiveness in financial market modeling.
(Millea, 2021)	A synopsis of DRL's uses in the cryptocurrency spaces. It frequently employs CNN and uses the Sharpe ratio to measure performance.
(Ferreira et al., 2021)	Examines AI's use in stock market trading between 1995 and 2019.
(Ashta and Herrmann, May 2021)	Covers the potential and hazards of AI in banking, investing, and microfinance. Presents a synopsis of AI's revolutionary impact on financial services.
(Milana and Ashta, 2021)	A review of the literature on AI in the financial markets. It examines studies on the effects of AI on growth, risk management, and market value. Additionally, it observes the recent rise in research on AI finance.
(Gogas and Papadimitriou, 2021)	Highlights small data set applications, predicting economic and financial factors. Moreover, it describes the novel uses of ML in finance and economics.
(Bayramoğlu, 2021)	Discusses AI's impact, benefits for regulatory authorities, and risks in Fintech.
(Aziz et al., Jun. 2022)	Utilize data science topic modeling to comprehend finance research and machine learning. It also identified fifteen study themes and grouped them into four categories.
(Chen et al., 2022)	Examines the integration of the disciplines of financial engineering and quantitative analysis, including deep learning. The study emphasizes valuable machine learning applications in finance and economics.
(Kurani et al., 2023)	Focuses on SVM and ANN for stock market forecasting. The study draws attention to these two methods' widespread use and effectiveness.
(Pallathadka et al., Jan. 2023)	An overview of the use of AI in finance and e-commerce. It discusses the impact of AI on quality control, efficiency, supply chains, and customer experiences.

4.1. Research questions

We aim to investigate how AI is utilized in financial trading, which primary machine learning algorithms are employed, how accurate they are, what makes a training model acceptable for the data presented, and which models provide the most return for traders. In addition, we want to look at the automation side of financial trading.

1. **RQ1: What are the trading market types studied in research? Which asset is being considered?**
2. **RQ2: Are fundamental or technical trading analysis approaches considered in the study? If so, what technical indicators are being used? What sources for fundamental analysis are being used? Does the proposed solution support automation?**
3. **RQ3: What type of AI approach is deployed? What are the techniques that are being used?**
4. **RQ4: What are the testing and evaluation metrics for the model performance?**

4.2. Search strategy

A thorough explanation of the search method used in this survey may be found below:

a) Search terms

The search phrases were determined by three factors: the research questions were utilized to determine the main search terms, fresh terms were discovered through specialized resources, and Boolean operators (ANDs and ORs) were used to limit the search results. The following are some of the search phrases that were used:

- "AI" **OR** "Artificial intelligence" **AND** "trading" **OR** "AI-based trading"
- "Machine learning" **AND** "trading"
- "Deep learning" **AND** "trading"
- "Deep neural network" **AND** "trading"
- "High-frequency trading" **AND** "artificial intelligence" **OR** "AI"
- "High-frequency trading" **AND** "machine learning"
- "Reinforcement learning" **OR** "transfer learning" **AND** "trading"

b) Survey resources

To find the needed research articles, the following digital libraries were consulted:

- IEEE Explorer
- Springer
- Elsevier Science Direct
- ACM Digital Library
- MDPI

c) Search phases

The research articles were retrieved from the relevant digital libraries using the above search criteria. We'll go through the inclusion/exclusion criteria in the next part. Based on the criteria we used for inclusion and exclusion, this study drew on 143 sources.

4.3. Study selection

Using the search criteria, we acquired a list of around 940 publications. However, after screening those publications to ensure that only those relevant to our research remained, we arrived at 143 papers published from 2015 to 2023. Figure 21 in Appendix A presents a distribution of the selected articles per year. The following is a description of the filtration and selection process:

1. Remove duplicate articles gathered from various libraries and authors.
2. Using inclusion and exclusion criteria, remove unnecessary articles and keep those that match inclusion criteria.
3. Maintain high-quality papers by including publications following quality evaluation guidelines.
4. Continue your search for comparable articles and repeat steps 3 and 4 on these new articles.

Table 4 shows the criteria used during the inclusion and exclusion phases.

4.4. Quality assessment rules (QARs)

Ultimately, QARs were employed to evaluate the acceptability of the articles obtained in answer to the study questions. There were 10 QARs

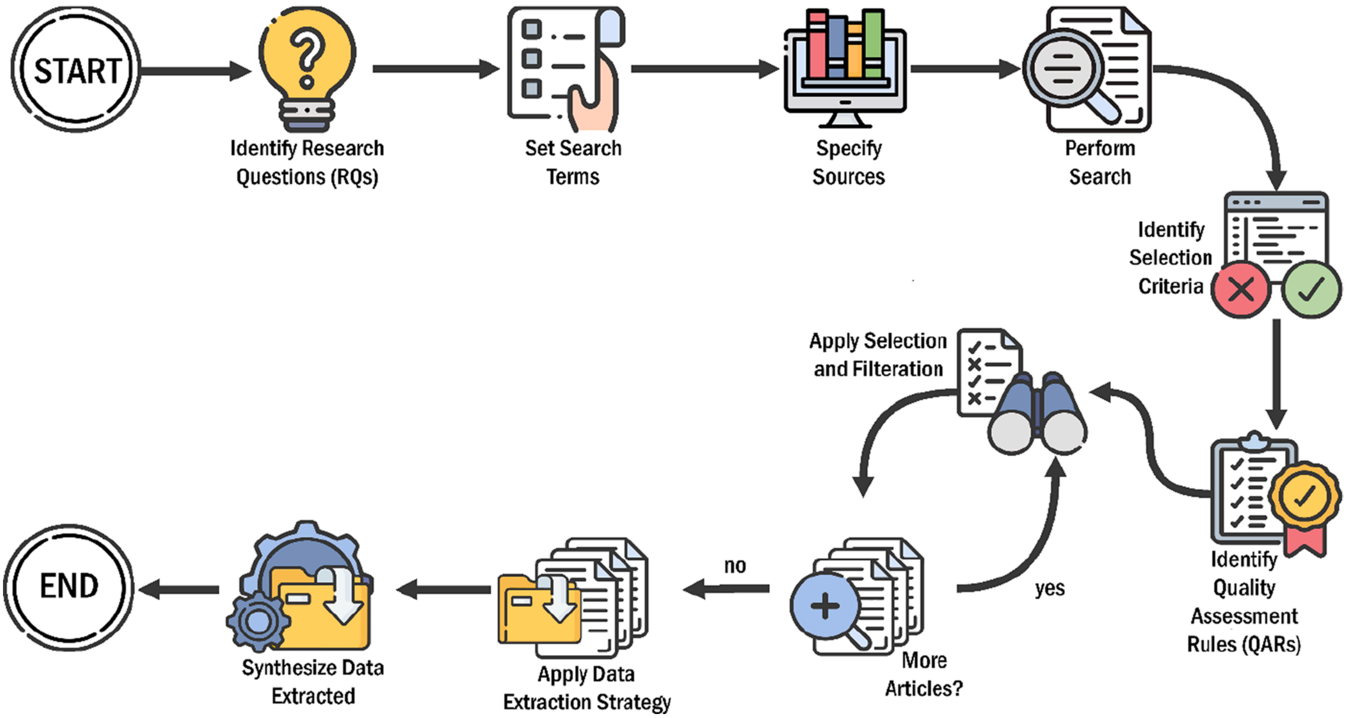

Fig. 3. The Stages of Performing Systematic Literature Review.

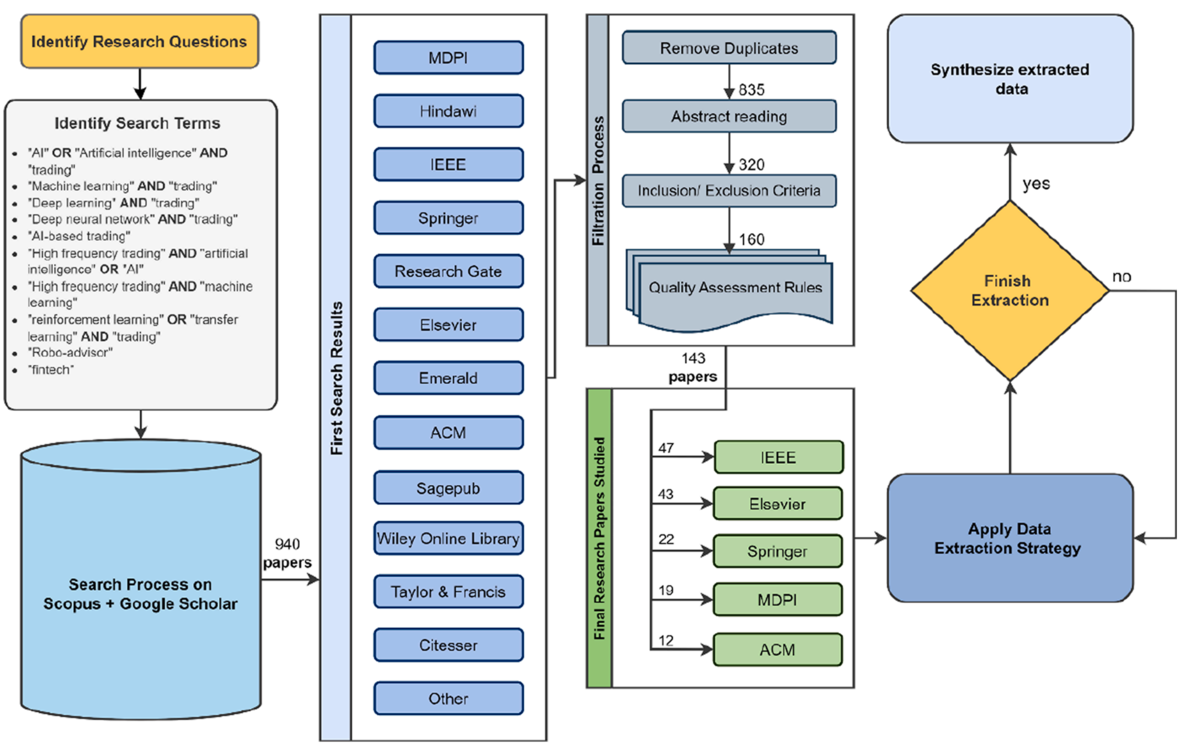

Fig. 4. Applied Research Methodology.

created, with each rule earning one point out of ten. The following formula was used to calculate the score: "completely responded" = 1, "above average" = 0.75, "average" = 0.5, "below average" = 0.25, and "not answered" = 0. The article's score is the total of the points obtained from all 10 QARs. If the result is five or above, the article is considered; otherwise, it is eliminated. Table 9 in Appendix A presents the selected research articles and the QAR score.

QAR1: Are the study objectives recognized?
QAR2: Is the trading asset identified?
QAR3: Is the type of trading strategy and approach defined?
QAR4: Are the strengths of the proposed methods well explained?
QAR5: Are the limitations of the proposed methods well explained?
QAR6: Are the methods well-designed and justifiable?
QAR7: Are evaluation metrics and testing results reported?

Table 4
Exclusion and Inclusion Criteria.

Exclusion criteria	Inclusion criteria
• Machine learning articles that aren't regarding financial asset price prediction, sentiment analysis, or portfolio optimization aren't included. Articles that do not use machine learning to predict pricing should be removed from consideration. Don't include any publications that haven't been peer-reviewed.	• Machine learning for price or trend predictions in financial assets, news, and social media sentiment monitoring and portfolio optimization. A study comparing machine learning and non-machine learning methods. Only take into account articles that were published in 2015. Only include articles from journals and conferences.

QAR8: Are the evaluation metrics of the proposed methods suitable?
QAR9: Is the evaluation metric compared to other methods?
QAR10: Overall, does the study enrich the academic community or industry?

4.5. Data extraction strategy

The completed list of articles was utilized to extract the information needed to address the set of research questions at this level. Paper ID, paper title, publication year, publication type, publisher source, RQ1 (Trading type, financial asset), RQ2(AI approach, Model, Automation), RQ3(analysis type, technical indicators, fundamental analysis source), RQ4(evaluation metric, testing, time frame, dataset), and RQ5(future work and challenges), were among the data retrieved from each paper. It's also worth mentioning that not all articles addressed the research questions. The following information was acquired from the selected research papers:

1) the financial market of trading (stock market, foreign exchange, cryptocurrency, future index, etc.).
2) the type of asset traded.
3) the AI approach is utilized (machine learning, deep learning, reinforcement learning, etc.), and the model is conducted.
4) the type of trading analysis used (fundamental analysis, technical analysis, trading strategy).
5) the features and output of the system (predicting exact price, predicting trend, or automating action).
6) the dataset utilized, source, and the time frame chosen.
7) the evaluation metrics of profitability and the performance of the model.
8) type of publication (journal, conference, or workshop).
9) the publication name.
10) the distribution of papers over the years.

4.6. Synthesis of extracted data

We employed several approaches to gather evidence that would answer the RQs from the data retrieved from the selected publications. The following section discusses the synthesis technique we used for each RQ.

We employed the narrative synthesis approach for RQ1-RQ3 and tabulated the data to create statistical comparisons between the various findings for each research question. In the case of RQ4, some retrieved data were qualitative, such as the type of assessment metrics, while others were quantitative, such as the period. Therefore, we utilized binary outcomes to compare the findings. Finally, for RQ5, future directions and difficulties are written in various ways using the reciprocal translation approach (Kitchenham, 2007), regarded as one of the qualitative data synthesizing strategies.

5. Results and discussion

In this section, we present the outcomes and findings of this SLR. This discussion is organized based on the RQs posed in the study. Before diving deeper into the analysis details, we provide Fig. 5, which presents a taxonomy of the results' structure to guide the reader through the following subsections.

5.1. Trading market types and asset types

In our investigation of the trading markets studied by researchers, we analyzed the selected research articles and plotted a histogram representing the frequency of these markets in Fig. 6. Our findings reveal that researchers have widely studied 8 different financial markets. The stock market emerged as the most extensively studied market among researchers. It is followed by the Foreign Exchange (FOREX) market and cryptocurrency trading, which also garnered significant attention in the literature. These three markets stand out as the primary focus of research efforts in the field. Furthermore, we identified six research articles that examined a combination of two markets. Some of these combinations were stock index futures with a commodity future market, stock markets with a commodity future market, stock markets with an exchange-traded Fund (ETF), stock markets with a bond market, and the stock market with cryptocurrency trading, as in (Taghian et al., 2022). By analyzing diverse trading markets, researchers aim to gain insights into the dynamics, patterns, and strategies specific to each market. This

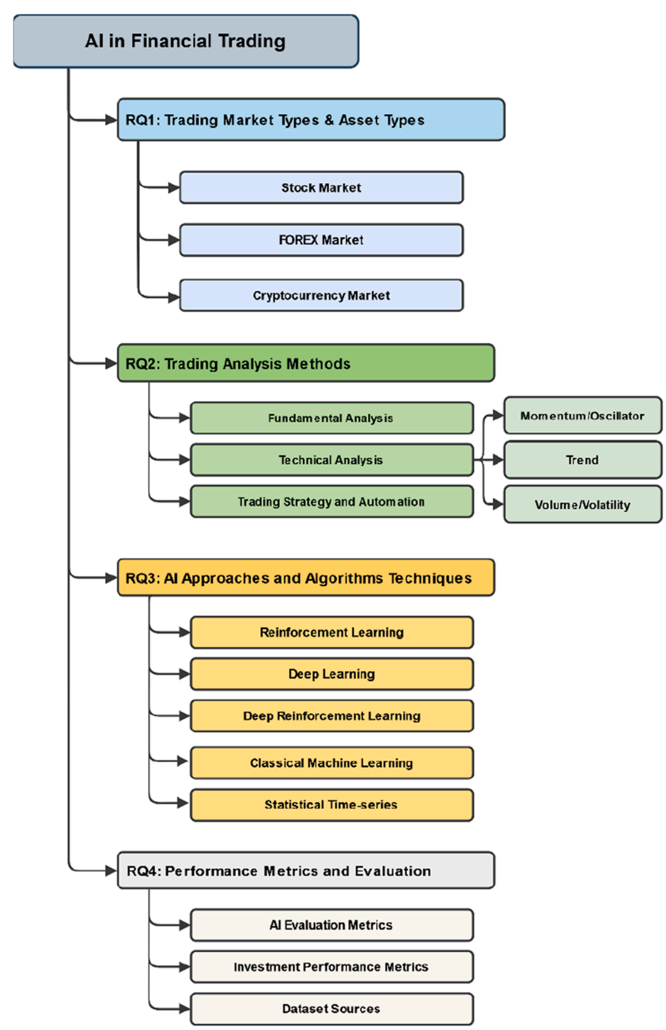

Fig. 5. Taxonomy of the Results and Discussion.

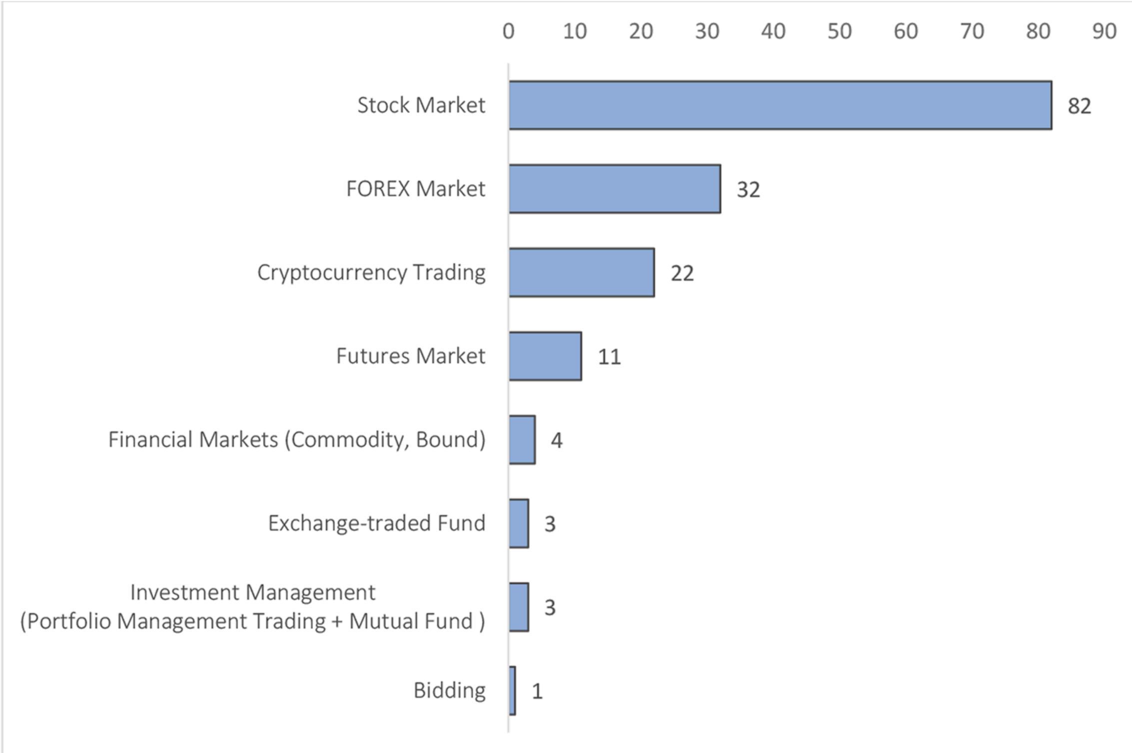

Fig. 6. Frequency Histogram of the Studied Trading Markets.

broader scope allows for a comprehensive understanding of different asset classes and their interrelationships, facilitating the development of more robust and adaptable trading models.

We have compiled the following findings in our analysis of the trading assets used in the stock market, FOREX market, and cryptocurrency trading. We categorized and examined the frequency of various assets, as detailed in Table 5. The categorization process involved classifying assets into distinct groups, such as major stock indices, exchanges and banks, tech companies, and miscellaneous entities. The findings shed light on the prevalence of these assets in the selected research articles. The table shows the frequency of stock indices utilized in the selected research articles. Of these indices, 21 research publications included the S&P 500 stock index as the most often used index. It was followed by eight research articles on the Nasdaq and the Dow Jones Industrial Average. The CSI300, FTSE, DJI, Nifty, SSE SZSE, and NYSE were among the other major stock indices mentioned in the studied research articles at different intervals, adding to the articles' broad representation of the world's stock markets.

The analysis of technology companies was one of the study's highlights. The analysis results indicated that tech business shares are more frequently used by researchers doing stock market experiments. The tech corporations that most commonly utilized the equities were Tesla (TSLA), Apple (AAPL), and Google (GOOGL). Seven studies discussed Google, compared to six that discussed Apple and one that used Tesla. Amazon (AMZN), Meta Platforms, and Microsoft (MSFT) are a few more significant tech firms that were utilized. Particular banks and stock exchanges also attracted attention in the study. Notable examples are the NSE stock price in India and the China stock market, which are covered in two and six research articles, respectively. The Taiwan Stock Exchange, B3 - Brazil Stock Exchange, and Taiwan Stock Index futures significantly broadened the range of international financial markets covered. Financial research predictions primarily focus on major stock indices, tech companies, exchanges, and banks, accounting for 61 %, 16 %, and 11 %.

In the FOREX market, trading involves currency pairs. Fig. 7 illustrates the most frequently traded currency pairs studied by researchers. The figure shows that the research articles' most widely utilized currency pairs are EUR/USD, GBP/USD, and EUR/GBP. Fig. 8 presents a pie chart depicting the distribution of currency frequencies in the selected research articles to explore further the utilization of individual currencies in the FOREX market. The figure highlights that the United States Dollar (USD), Euro (EUR), and Pound Sterling (GBP) were the most commonly studied currencies, accounting for 26 %, 22 %, and 13 % of the research articles, respectively. On the other hand, the Singapore Dollar (SGD) and Chinese Yuan (CNY) were among the least studied currencies in the FOREX market.

In the cryptocurrency market, Fig. 9 provides an overview of the distribution of digital currencies utilized in the selected research articles. Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC) were the most frequently involved digital currencies, appearing in 19, 9, and 8 research articles, respectively. It is worth mentioning that some researchers studied cryptocurrency pair exchanges. For example, several research articles implemented the BTC-USDT pair in their application of AI techniques in cryptocurrency trading, as mentioned in (Sun et al., 2019) and (Corletto et al., 2021).

By examining these specific trading assets in each market, researchers aim to gain insights into their unique characteristics, market behavior, and potential trading strategies. This detailed analysis enables the development of more targeted and effective AI-based trading models within each market context.

5.2. Trading analysis methods

In this research question, we aim to explore the implementation of different trading analysis types in conjunction with AI techniques. Fig. 10 provides insights into the frequency of trading analysis types utilized in implementing AI in trading markets. According to the figure, technical analysis, trading strategy, and fundamental analysis are the primary analysis methods implemented in conjunction with machine learning techniques. Among these, technical analysis is the most widely utilized, appearing in 71 % of the selected papers. On the other hand, fundamental

Table 5
Frequency of Stock Assets Utilized.

Category	Stock	Freq.	Category	Stock	Freq.
Major Stock Indices	S&P 500	21	**Other Companies**	IBM	1
	30 Dow	8		RDSB	1
	Nasdaq	8		CICI Bank	1
	CSI300 index	4		AXP	1
	FTSE index	3		KSS	1
	DJI	3		ULVR	1
	Nifty	3		**Percentage**	**6 %**
	SSE and SZSE	5			
	NYSE	2	**Exchanges and Banks**	China stock market	6
	BSE SENSEX	2		Indian stock price NSE	2
	OMXS30	1		Taiwan stock index futures	2
	VN-index	1		Taiwan Stock Exchange	1
	Shanghai Composite Index	1		B3 - Brazil Stock Exchange	1
	EuroStoxx50	1		**Percentage**	**11 %**
	Moscow Stock Exchange index	1			
	Sao Paulo stock exchange index	1	**Tech Companies**	GOOGL	7
	Percentage	**61 %**		AAPL	6
Miscellaneous	BATS	1		TSLA	1
	RTS Index	1		MSFT	1
	HDI	1		AMZN	1
	EuroStoxx50	1		Meta Platforms	1
	Shanghai Composite Index	1		**Percentage**	**16 %**
	Percentage	**6 %**			

analysis is employed in 12 % of the research papers, indicating a lesser prevalence than technical analysis. Additionally, 5 % of the research papers combine technical and fundamental analysis. Furthermore, a subset of research papers, 1 %, focuses on specific trading strategies while also studying the impacts of news, which falls under the realm of fundamental analysis. Incorporating news sentiment and its impact on trading decisions is particularly valuable. As well as, 1 % of papers focus on trading strategy with technical analysis implementation.

When obtaining news data for fundamental analysis, the most widely used sources include Bloomberg, Thompson Reuters' news sentiment, and Yahoo Financials. These sources provide researchers with the necessary information to study and analyze the impact of news on financial markets. Using different trading analysis types with AI techniques reflects researchers' diverse approaches to enhancing trading strategies. While technical analysis dominates the implementation landscape, fundamental analysis, trading strategies, and combining these methods showcase the integration of AI techniques in exploring various aspects of trading markets.

To analyze the frequency of technical indicators used in the selected research articles, we present Fig. 11. The figure categorizes the technical indicators into three main types: Momentum/Oscillator, Trend, and Volume/Volatility, in addition to Table 6, which presents the frequency of each technical indicator type.

Momentum indicators are commonly employed to assess the strength or weakness of an asset's price. These indicators help identify the rate at which prices increase or decrease. The frequently used momentum indicators in the selected papers include the Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Commodity Channel Index (CCI). These indicators provide insights into the momentum of price movements and help traders make informed decisions.

Trend indicators are utilized to determine the direction of a trend. These indicators assist in identifying whether the market is experiencing an upward or downward trend. Some of the trend indicators commonly employed in the selected papers are the Moving Average (MA), Simple Moving Average (SMA), and Exponential Moving Average (EMA). These indicators provide valuable information about the trend's direction and potential reversals.

Volume indicators are crucial in assessing an asset's bullish and bearish strength. They help analysts determine the buying and selling

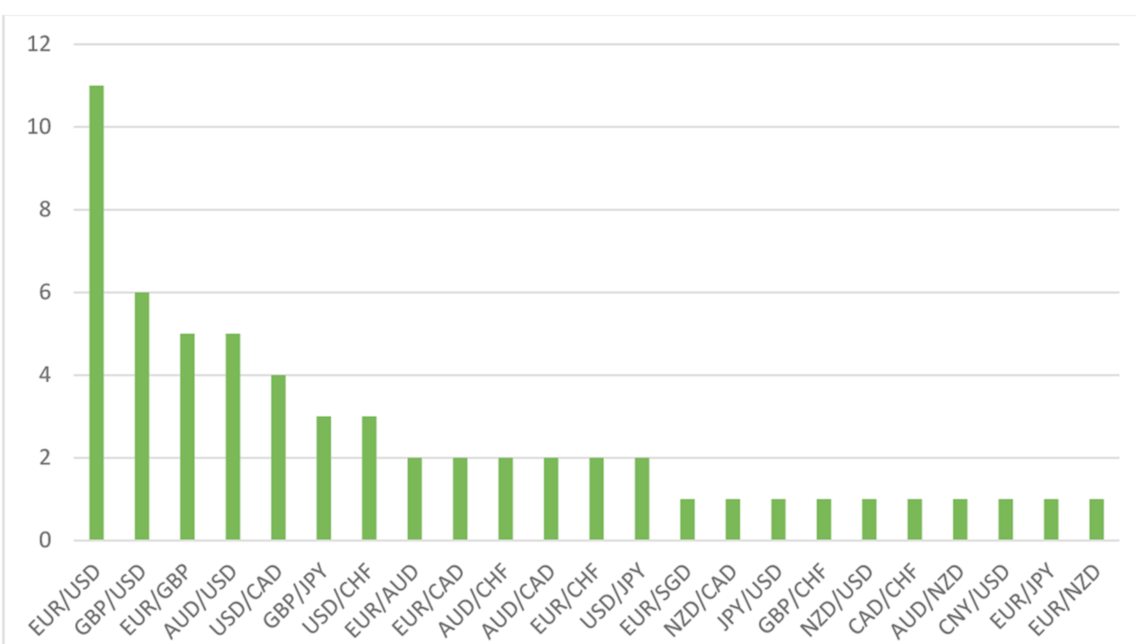

Fig. 7. FOREX Currency Pairs Frequency Distribution.

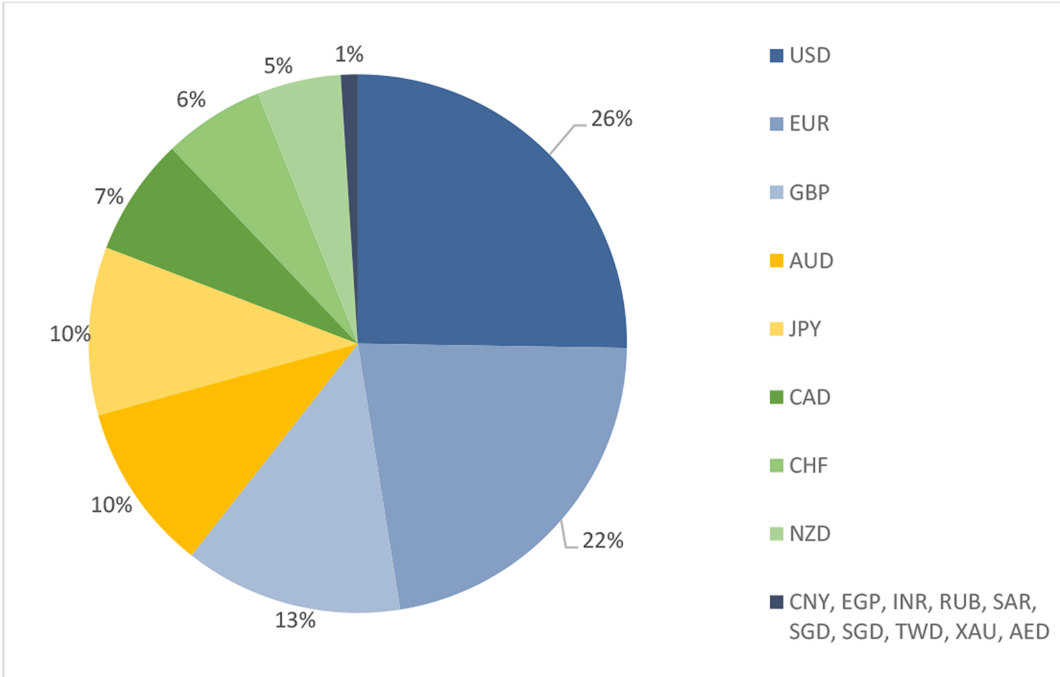

Fig. 8. Currency Trading Frequency.

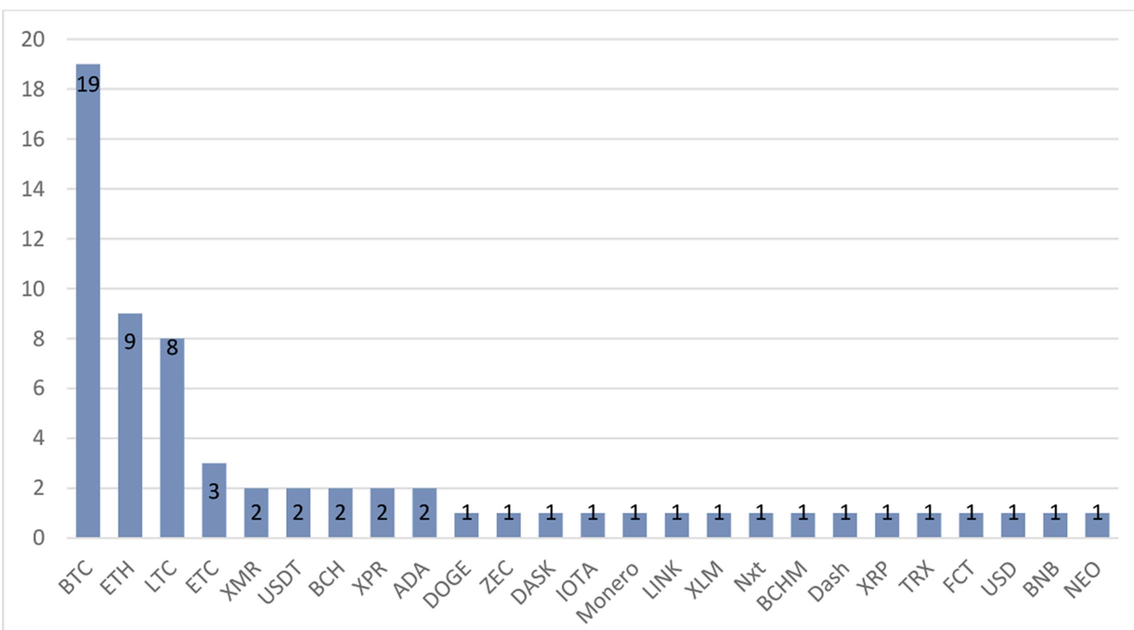

Fig. 9. Cryptocurrency Frequency Distribution.

pressure in the market. Volume indicators gauge the level of activity and participation in a particular security. Examples of volume indicators employed by researchers include Balance Volume (OBV), Average True Range (ATR), Positive Volume Indicator (PVI), and Negative Volume Indicator (NVI). These indicators help traders understand the emotions and sentiments driving market participants.

Volatility indicators aid in identifying periods of high or low volatility in a specific market. They help traders assess the level of risk and potential price fluctuations. Volatility indicators employed by researchers include Average True Range (ATR), Bollinger Bands, and Standard Deviation. Various technical indicators in the selected papers demonstrate the importance of analyzing price movements and market dynamics. By incorporating momentum, trend, volume, and volatility indicators, researchers aim to gain insights into market behavior and make more informed trading decisions.

Market information, commonly called OHLC (Open, High, Low, Close), is the primary input for any model. The ’Open’ represents the initial price of an asset, while the ’Close’ signifies the final price. The ’High’ denotes the peak price reached, whereas the ’Low’ indicates the minimum price observed during the asset’s market activity. The data’s

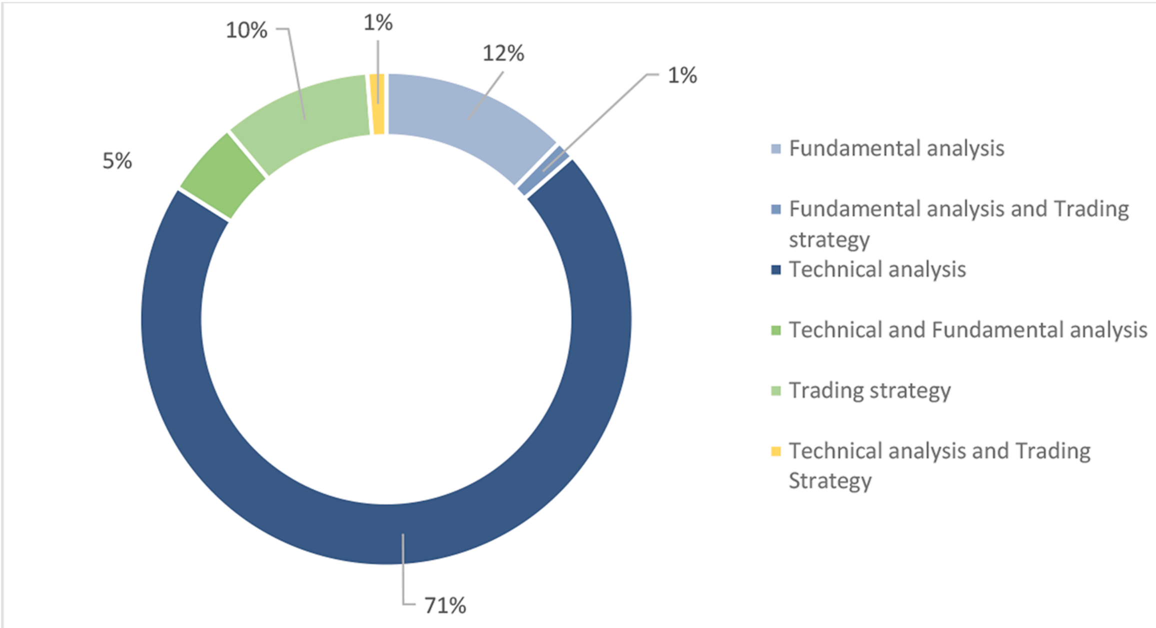

Fig. 10. Trading Analysis Methods Implemented in Selected Research Articles.

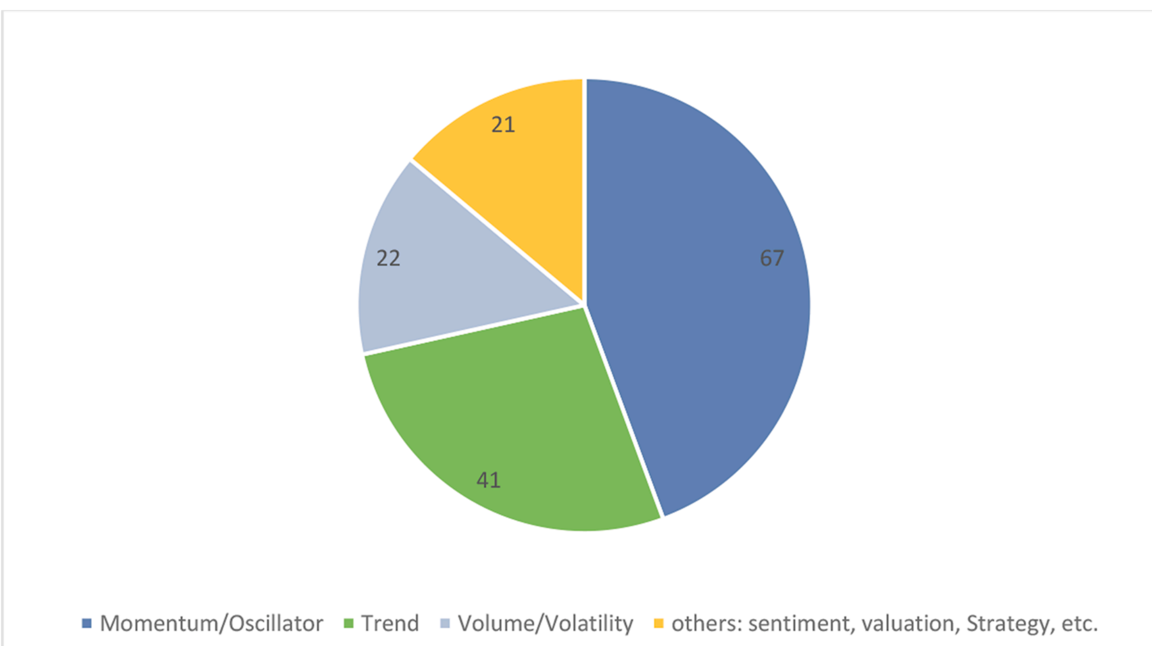

Fig. 11. Technical Analysis Indicators Types Frequency.

Table 6
Methods Implemented in Each Indicator Type.

Indicator Type	Frequency	Method
Momentum/Oscillator	67	RSI, MACD, CCI, etc.
Trend	41	MA, SMA, EMA, etc.
Volume/Volatility	22	OBV, ATR, PVI, NVI, etc.
Others: sentiment, valuation, Strategy, etc.	21	ISE, P/CF, stop loss strategy, etc.

granularity varies depending on the timeframe for which prices are collected, ranging from yearly, monthly, weekly, daily, and hourly to minute-by-minute intervals.

The choice of data granularity relies on the intended prediction goals. For long-term investments, opting for lower granularity data, such as monthly or weekly intervals, can help smoothen out signals, reduce noise, and minimize computational requirements due to a smaller dataset size. Conversely, short-term investments and intraday scalping strategies benefit from higher granularity data. However, it's important to note that higher granularity data introduces more noise, although it enables the model to capture additional signals. Thus, striking a balance between noise and signal ratio becomes crucial.

It's worth highlighting that selecting the appropriate data granularity and dataset size involves a trade-off between capturing relevant information and managing computational resources. Finding the right balance that aligns with your specific requirements and trading strategy is paramount.

In addition to market price data, researchers commonly incorporate various trading analysis types into their prediction models. Technical analysis involves the inclusion of specific indicators that align with their investment plan, in addition to the primary market price, as input for training the models. On the other hand, some researchers employ fundamental analysis, which entails web scraping news articles to identify factors that influence prices. They combine this news data with market information for their models. Another approach is to leverage technical and fundamental analysis with market data.

The outputs of these models vary among researchers, but the ultimate goal is to maximize profitability. Some researchers adopt a strategy that determines the most suitable time for actions such as buying, selling, or holding based on the model's predictions using historical data. Others focus on predicting the overall trend, whether upward or downward, while some aim to predict the recommended position for the trader, such as long, short, or holding the position. Alternatively, some models focus on predicting the price or emphasize success and profit rates. Fig. 12 illustrates the model's different approaches as input and output.

Some of these models incorporate automation by directly executing the predicted actions. Fig. 13 showcases the percentage of papers that implemented automation and developed a fully functional trading system. Interestingly, more than half of the examined research papers did not employ automation in their solution. Only 16 % of the research papers automated the actions predicted by their models. However, 22 % of the solutions implemented an agent-based system, where the model learns and improves its performance through interactions with the trading environment. This approach allows for adaptive decision-making based on real-time feedback.

5.3. AI approach and algorithm techniques

One of the key findings of our study was to identify the most commonly employed AI techniques in the financial trading sector. Throughout the different stages of the experiments, including feature extraction, preprocessing, and analysis, we thoroughly examined the methodologies and implementations described in the literature.

Fig. 14 categorizes the AI approaches used in trading financial markets, which can be classified into five primary types: classification, regression, deep learning, reinforcement learning, and deep reinforcement learning. Each approach is described below, along with its financial trading application:

- **Classification:** Ten percent of the articles we reviewed used classification techniques, which included categorizing data into predetermined classes or categories. These algorithms could be used in trading to categorize possible trades into "buy" or "sell" groups based on their ability to forecast an asset's price movement.
- **Regression:** Regression methods are used in 2 % of the chosen articles to forecast continuous outcomes, like a stock's future price. Regression analysis can offer essential insights into price patterns and fluctuations in the market despite its lower adoption rate.
- **Deep Learning:** The most widely used strategy, used in 30 % of the articles, deep learning algorithms can process enormous amounts of unstructured data, which makes them especially helpful for identifying complex trading patterns, predicting price movements, and analyzing market sentiment.
- **Reinforcement Learning:** 29 % of the articles use this technique, in which algorithms are trained to find the best course of action through trial and error to maximize the total reward. These algorithms can optimize for long-term gains in trading by dynamically modifying strategies in response to market performance.
- **Deep Reinforcement Learning:** This strategy, also used in 29 % of the studies, combines reinforcement learning's ability to make decisions with deep learning's capacity for pattern recognition. As a result, it is perfect for creating autonomous trading systems that can adjust to shifting market conditions.

These results indicate that, in this domain, deep learning, reinforcement learning, and combinations of them are preferred and considered more appropriate than classification and regression techniques. The fondness for these approaches emphasizes how complicated financial markets are and how sophisticated AI methods that can comprehend and adjust to changing environments are required.

Fig. 15 offers further insights into the distribution of methodologies used in financial trading markets over the years. It reveals that deep reinforcement learning started gaining attention in 2019 and reached its highest popularity among researchers in 2020. On the other hand, reinforcement learning was the most commonly used approach in 2018 and 2021, but it was surpassed by deep learning in 2022.

Fig. 16 provides an overview of the AI techniques and algorithms for predicting financial trading markets. Our study identified nearly 40 main techniques from the research articles examined. These techniques can be broadly categorized into four approaches: statistical time-series analysis, classical machine learning, deep learning, and reinforcement learning.

For the statistical time series category algorithms such as autoregressive with moving average. A copula statistical method is frequently applied in risk analysis and financial modeling. It is mainly used to simulate the relationship between many random variables. When the marginal distributions of the variables are known, but the dependence structure is too complex for conventional statistical techniques to represent, copula functions enable the modeling of complex interactions between the variables. Copula is a statistical time-series analysis tool that can be used in the context of AI. However, it is a statistical analysis tool rather than a specialized AI technique. It can be combined with AI approaches like machine learning, deep learning, or reinforcement

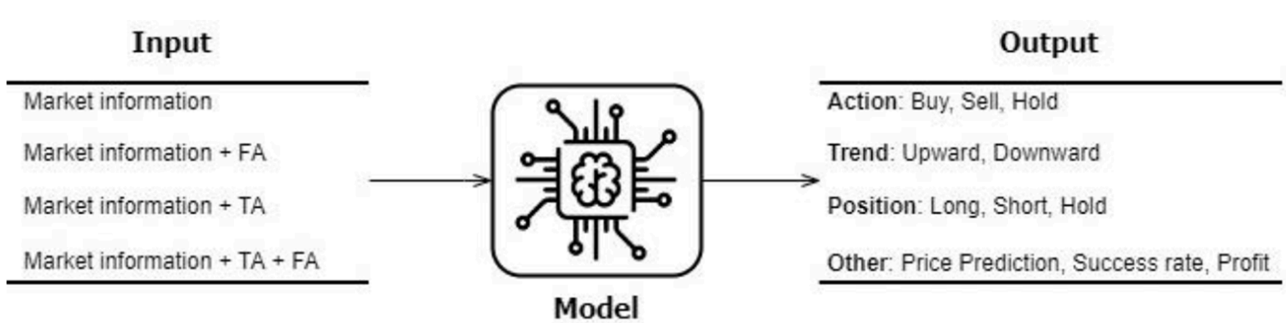

Fig. 12. Utilizing Trading Analysis in AI.

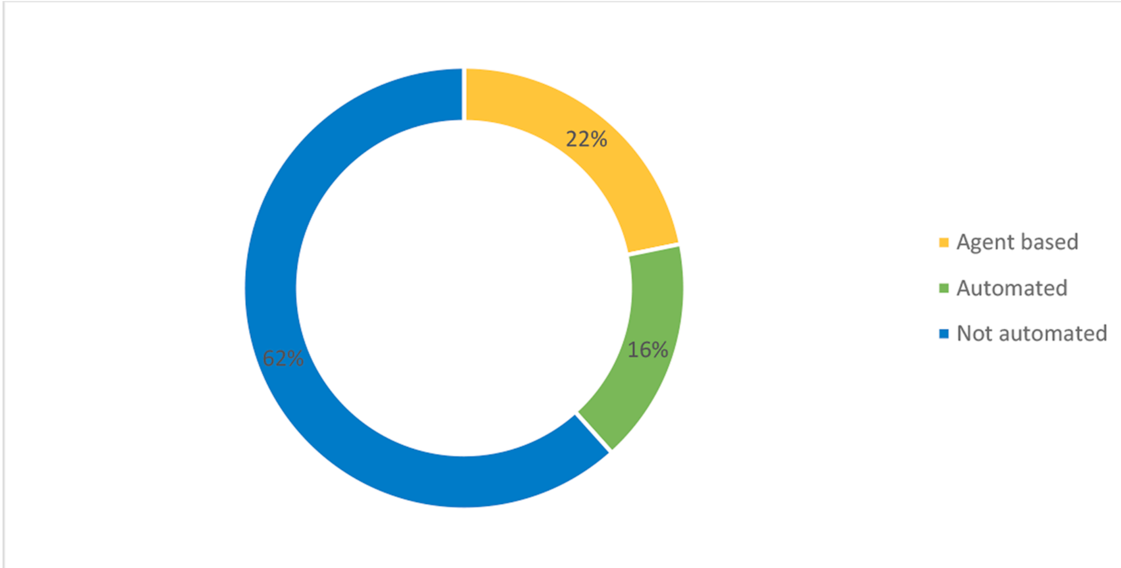

Fig. 13. The Percentage of Automated Solutions of Selected Research Articles.

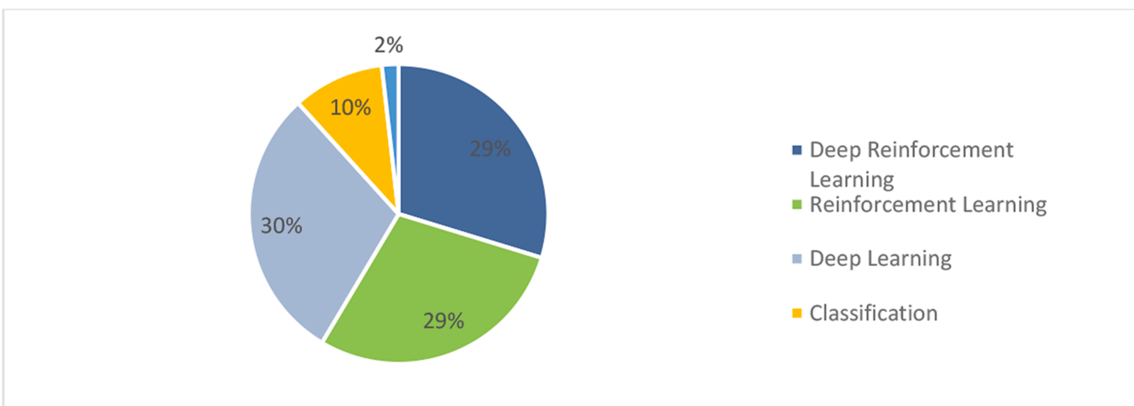

Fig. 14. AI Type Implementation by Selected Research Articles.

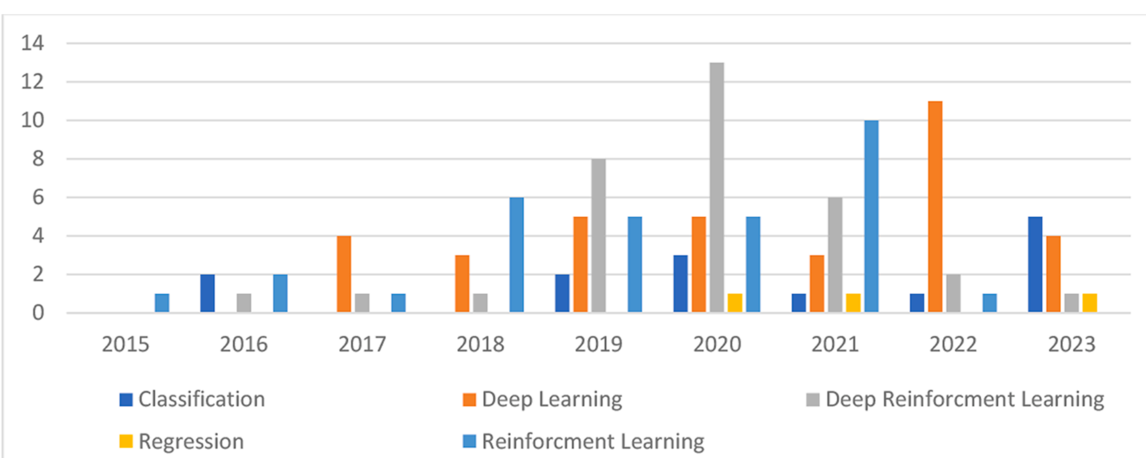

Fig. 15. Distribution of AI Implementation Types per Year.

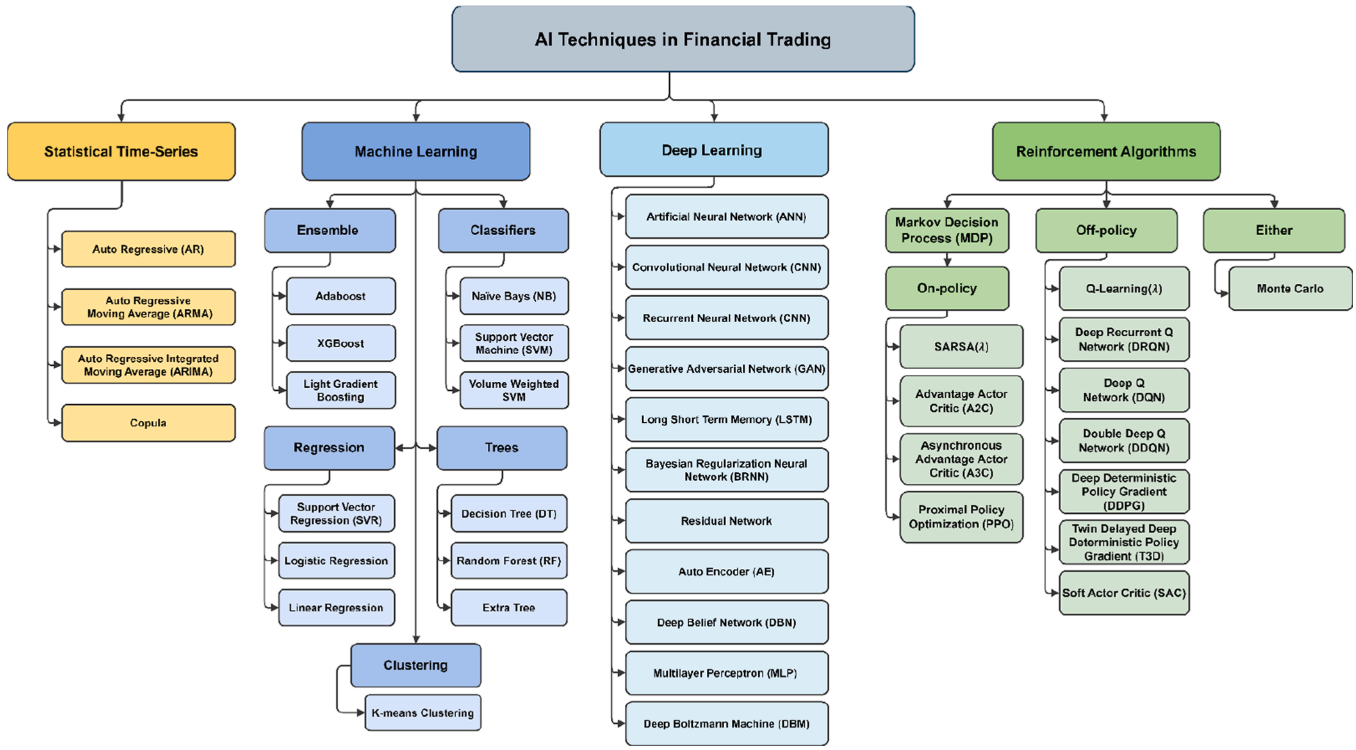

Fig. 16. AI Techniques utilized in Financial Trading Markets.

learning to improve financial trading modeling and prediction capabilities.

We divided the algorithms into classifies, ensemble, regression, and clustering in classical machine learning. Deep learning techniques have gained significant attention in financial trading—neural network algorithms such as convolutional neural networks, recurrent neural networks, and generative adversarial networks. Notably, the use of Long Short-Term Memory (LSTM) networks has been prevalent due to their ability to capture temporal dependencies. Reinforcement learning approaches have also gained prominence in financial trading prediction. Reinforcement learning algorithms can be based on policies, either on-policy or off-policy. Noteworthy algorithms include Deep Q Network (DQN), Deep Deterministic Policy Gradient (DDGP), and actor-critic algorithms. These Reinforcement learning techniques have been applied to develop effective trading strategies by learning from interactions with the trading environment.

It is worth mentioning that many research articles implement hybrid approaches, combining multiple algorithms. For instance, in (Yuan et al., 2020), a hybrid implementation of Proximal Policy Optimization (PPO) with DQN and Soft Actor-Critic (SAC) was utilized. Feature selection was performed using clustering techniques, and Twin-Delayed Deep Deterministic Policy Gradient (TD3) was employed (Park and Lee, 2021). Moreover, one paper utilized a transformer model known as finBERT to incorporate fundamental analysis by studying the sentiments of news headlines. Alongside this, LSTM, CNN, and Multilayer Perceptron (MLP) algorithms were employed for predictions (Passalis et al., 2021).

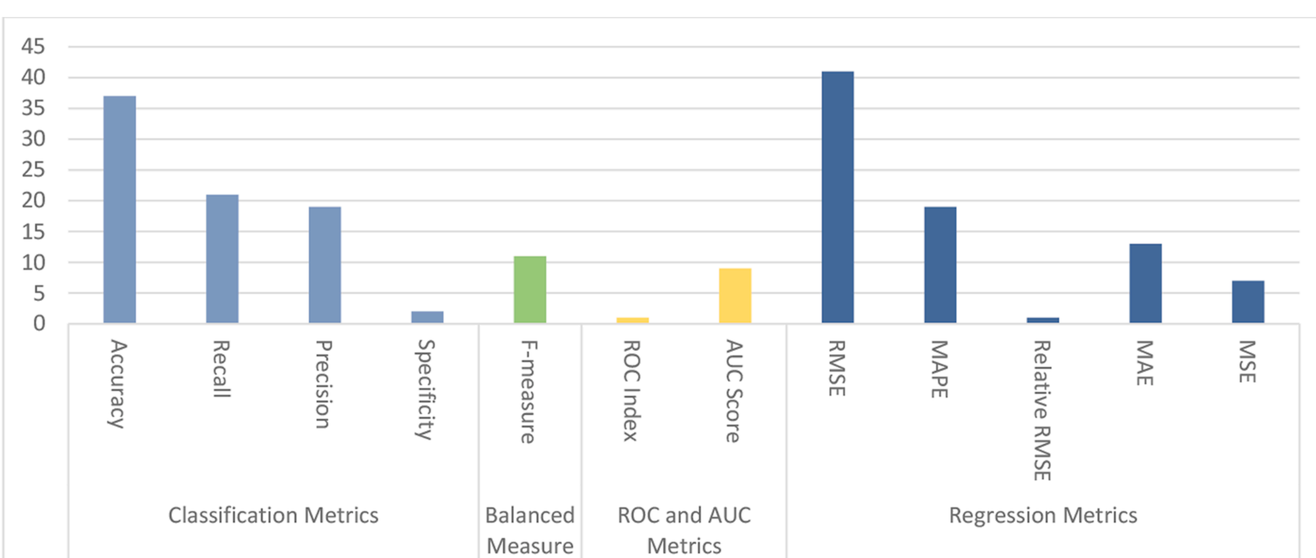

Fig. 17. Frequency of AI Evaluation Metrics.

These diverse techniques and hybrid approaches highlight the evolving nature of AI applications in financial trading, encompassing statistical, machine learning, deep learning, and reinforcement learning methods. The selection and combination of these techniques depend on the specific research objectives and the characteristics of the financial markets being analyzed.

5.4. Performance metrics and evaluation

Evaluation of model performance is a crucial step in any AI pipeline workflow. In this research question, we aim to investigate the performance metrics commonly adopted to measure and evaluate the efficiency of the proposed methods and techniques. Several well-known AI evaluation metrics are specifically designed to assess the quality of model predictions. Fig. 17 provides insights into the frequency of evaluation metrics used to test the performance of AI models. According to the figure, the most commonly adopted metrics among classification include accuracy, recall, and F-measure. Notably, many research articles employ a combination of two or more of these evaluation methods. Furthermore, several researchers compare the performance of their proposed approach with a zero-intelligence strategy, which involves simply buying and selling. This comparison highlights the advantages of using an AI approach over a traditional buy-and-hold strategy. The most widely used evaluation metric is Root Mean Square Error (RMSE), categorized as a regression metric.

However, it is essential for researchers to evaluate the model from a financial perspective as well. To address this aspect, we present Table 7, which showcases the most commonly used performance metrics for assessing financial performance. The metrics include the Sharpe Ratio, Rate of Return (RoR), Maximum Drawdown, and Total Return. These metrics provide insights into the proposed models' risk-adjusted returns, overall profitability, and financial viability. Adopting evaluation metrics from both AI and financial perspectives ensures a comprehensive assessment of model performance, encompassing both the accuracy of predictions and the financial gains or losses associated with the proposed strategies.

Validating the performance of a trading strategy involves several prominent testing methodologies. Backtesting is a widely utilized and robust assessment method. Backtesting consists of testing a prediction model's performance on additional historical data. It allows traders to evaluate the effectiveness of their strategies without risking actual capital. Backtesting provides valuable insights into how well the model would have performed in the past. Conversely, forward testing enables real-time replication of trading strategies as new data becomes available. It is also referred to as paper trading, as it simulates real-world trading conditions without using actual funds. Forward testing provides traders with an additional sample to analyze that is not derived from the historical data used in backtesting.

While both backtesting and forward testing are commonly employed, backtesting is more widely adopted in the literature. Approximately 28 papers performed backtesting to validate their trading strategies, as exemplified by (Kim, Aug. 2021). On the other hand, a smaller number of research papers, around 5, utilized forward testing to assess their strategies, as demonstrated in (Żbikowski, 2016). These testing methodologies play a crucial role in evaluating the performance and viability of trading strategies, providing traders with valuable insights into their effectiveness under historical and real-time conditions.

During our study, we identified 30 sources of datasets that researchers utilize to obtain their data. Table 8 presents a list of these sources and their frequency of utilization in the selected research articles. Based on the table, Yahoo Finance emerges as a reliable and commonly used source for obtaining market data. Its comprehensive coverage and availability make it a popular choice among researchers. Additionally, Tushare, a Chinese source that employs web crawling techniques to gather historical financial data, was utilized by 4 research articles. This highlights its significance as a valuable data source for studying financial markets. Furthermore, Bloomberg and Google Finance are reputable sources for obtaining historical financial data. These sources offer extensive financial information and are considered reliable by researchers in the field. The utilization of various data sources reflects researchers' diverse needs and preferences in obtaining the necessary datasets for their studies. The selection of a particular data source depends on factors such as data coverage, reliability, accessibility, and specific research requirements. Overall, Yahoo Finance, Tushare, Bloomberg, and Google Finance are among the prominent sources frequently mentioned in the literature for acquiring historical market and financial data.

To examine the impact of market crises on the selected papers, we investigated the year ranges of the datasets used. Fig. 18 provides insights into the years covered by the datasets in the selected research papers. Based on the figure, it is evident that most selected papers adopted either a 4-year or 1-year range of market data. This indicates that researchers often focus on relatively recent data to analyze market trends and patterns. Furthermore, some papers considered a 10-year range, suggesting a longer-term perspective. However, it is worth noting that a few papers took a significantly more extensive time range

Table 7
Frequency of Investment Performance Metrics.

Investment performance	Freq.	%	Investment performance	Freq.	%
Sharpe Ratio	53	18 %	Return on Investment (ROI)	4	1 %
Rate of Return (RoR)	37	12 %	Value at Risk (VaR)	3	1 %
Maximum Drawdown	30	10 %	Winning Rate	3	1 %
Total return	30	10 %	Information ratio	3	1 %
Total profit (Net profit)	26	9 %	Maximum Capital	2	1 %
Yield volatility	23	8 %	Calmar Ratio	2	1 %
Average profit	16	5 %	Sterling ratio	2	1 %
Profit and loss diagram	16	5 %	# of positions/actions	2	1 %
Sortino Ratio	14	5 %	Minimum Capital	1	0 %
# of transactions	13	4 %	Excess return rate	1	0 %
Cumulative returns	12	4 %	Accumulated portfolio value	1	0 %
Loss percentage	6	2 %	Kolmogorov-Smirnov statistics	1	0 %

Table 8
Frequency of Dataset Source.

Source of Dataset	Freq.	Source of Dataset	Freq.
Yahoo Finance	18	International Settlements Triennial Central Bank	1
Investing.com	5	FactSet Research Systems	1
tushare	4	SpeedLab AG	1
Dukascopy bank	4	Bombay Stock Exchange	1
kaggle	4	AlphaVantage service	1
Metatrader	4	kaiko	1
Bloomberg	3	Bitstamp	1
Google Finance	3	Global-View Forex Forum	1
Wharton Research Data Services	2	Bincentive	1
Binance	2	National Stock Exchange	1
Thomson Reuters	2	Quandl API	1
Wind Database	2	Market Watch	1
Shanghai Stock Exchange	2	Binance	1
Nasdaq	2	CoinMarketCap	1
Taiwan Stock Exchange	2	Fxtree	1

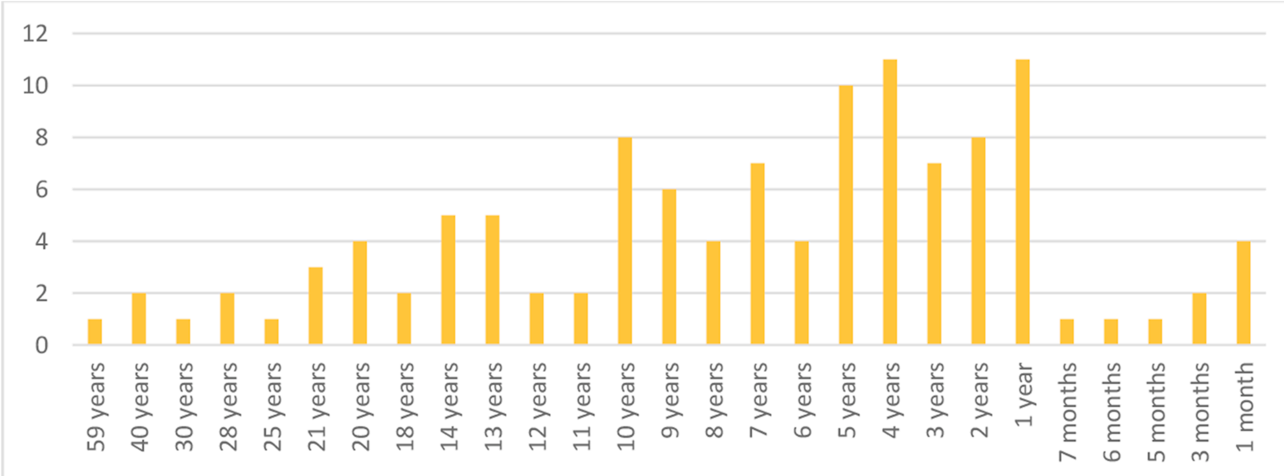

Fig. 18. Year Period Range of Selected Dataset.

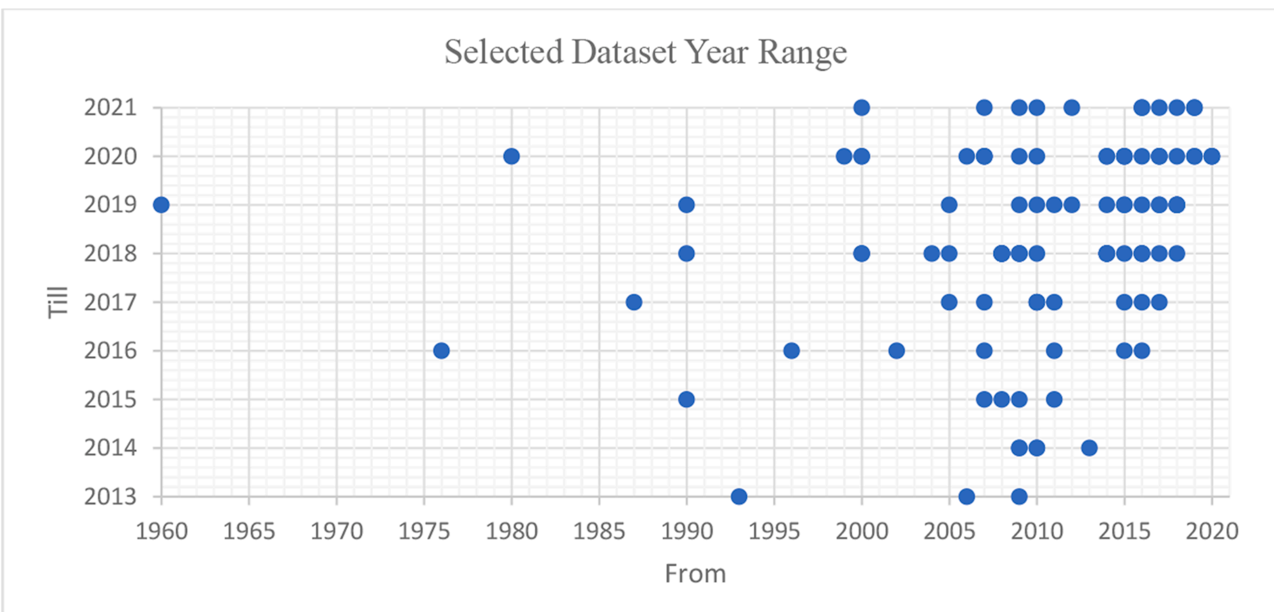

Fig. 19. Selected Dataset Year Range.

Fig. 20. Timeline of Crisis Events that Effected US Stock Market Provided by Sabrina Jiang (Williams, 2022).

for their datasets. For instance, (Hirchoua et al., May 2021) considered a range between 1960 and 2019, reflecting a comprehensive historical perspective. Additionally, (AbdelKawy et al., 2021) and (Pendharkar and Cusatis, 2018) utilized datasets spanning 40 years, from 1980 to 2020 and 1976 to 2016, respectively. These papers aimed to capture long-term trends and investigate the impact of crises over a broader time frame. Fig. 19 presents the starting and ending years of the dataset ranges, providing a visual representation of the period covered by the selected papers. This visualization helps understand the specific periods researchers chose for their analyses. Furthermore, Fig. 20 showcases the main crisis events timeline, illustrating the occurrence of significant market crises. This timeline can be used to observe how researchers select their dataset ranges, considering periods that include crises known to affect market prices. The choice of dataset year range allows researchers to focus on specific periods of interest, providing insights into the impact of market crises and trends within those periods.

6. Conclusion

This systematic literature review studied financial trading approaches through AI techniques. It reviews 143 scientific research articles implementing AI techniques in financial trading markets. Accordingly, it presents several findings and observations after reviewing the papers from the following perspectives: the financial trading market and the asset type, the trading analysis type considered along with the AI technique, and the AI techniques utilized in the trading market, the estimation and performance metrics of the proposed models. The selected research articles were published between 2015 and 2023, and this review addresses four RQs.

The results of the first RQ were that we identified 8 financial markets utilized for the application of AI. The most widely studied markets are the stock market, the FOREX market, and Cryptocurrency Trading, respectively. Furthermore, S&P stocks are the most utilized assets in the stock market, and the currency pair in FOREX is EUR/USD. As for cryptocurrency, the digital currency used the most is BTC. The second RQ's findings were that technical analysis indicators are preferable to fundamental analysis. In addition, fundamental analysis is adopted even more than trading strategies. Moreover, the most used type of technical indicator is momentum/oscillators, especially the RSI. On top of that, these analysis methods in AI are market information that is given for the model and used as input with trading technical indicators, fundamental analysis, or both types. As well as an interesting finding is that only 16 % of these solutions entirely automate the trading process. Moving on to the third RQ, the AI approach widely implemented for building predictive models is deep learning, which is utilized by 30 % of the papers, followed by reinforcement learning and deep reinforcement learning, which are each used by 29 % of the research papers. We provided a distribution of these approaches per year, and we identified 40 main AI techniques in this domain, which are used mostly as hybrid models that combine more than 2 of these algorithms. Finally, the fourth RQ presented the evaluations of these approaches from two aspects: a model performance evaluation and an investment evaluation. RMSE, Accuracy, recall, and F-measure are the most common model evaluation metrics used. Sharpe ratio, rate of return, maximum drawdown, and total return are the most commonly utilized investment evaluations. Furthermore, Yahoo Finance is the most extensive dataset source from which researchers have obtained market information. The time-series data studied used a 4-year and 1-year data range the most. We present the years that included crises worldwide that affected the prices.

Because of their vast dimensionality and various social impacts, financial markets are thought to be highly frequented and vulnerable to risky actions. As a result, we recommend that researchers focus more on the models' risk-controlling behavior and build additional crisis detectors so they can perform more risk-aversion selections. Furthermore, the study discovered that building an approach for determining the best model training duration is needed. Finally, future work will include developing an automated financial trading system that incorporates both fundamental and technical analysis into the prediction model and comparing it to one of the methodologies described in the study publications.

Competing interests

We confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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CRediT authorship contribution statement

Fatima Dakalbab: Methodology, Software, Formal analysis, Data curation, Investigation, Resources, Visualization, Writing – original draft. **Manar Abu Talib:** Conceptualization, Validation, Funding acquisition, Writing – review & editing, Supervision. **Qassim Nassir:** Conceptualization, Resources, Project administration, Supervision, Writing – review & editing. **Tracy Saroufil:** Formal analysis, Data curation, Investigation, Resources, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table 9
QAR results of the Selected Papers.

Score	No. of paper	Ref.
5.5	1	(Koker and Koutmos, 2020)
5.75	1	(Leles et al., 2019)
6	4	(Fallahpour et al., 2016); (Ugur Gudelek et al., 2017); (Zarkias et al., 2019); (Sidehabi, 2016)

(*continued on next page*)

Table 9 (*continued*)

Score	No. of paper	Ref.
6.75	5	(Pendharkar and Cusatis, Aug. 2018); (Wu et al., 2019); (Bisi et al.); (Chen et al., 2020); (Chen et al., Nov. 2021)
7	5	(Chen et al., 2018); (Sun et al., 2019); (Chen and Gao, 2019); (Maalla et al., 2021); (Vogl et al., 2022)
7.25	4	(Yong et al., 2017); (Si et al., 2017); (Jeong and Kim, 2019); (Tsantekidis et al., 2020-September, Sep. 2020)
7.5	11	(Ma and Han, 2018); (Carapuço et al., Dec. 2018); (Dang, 1121); (Li and Peng, 2019); (Baek et al., 2020); (Bisht and Kumar, 2020); (Di. Fengqian and L. Chao, , 2020); (Wang et al., May 2021); (Hamayel and Owda, Oct. 2021); (Srivinay et al., May 2022); (Sharma and Shekhawat, 2022)
7.75	5	(Deng et al., Mar. 2017); (Jirapongpan and Phumchusri, 2020); (Lahmiri and Bekiros, Apr. 2020); (Zhang, May 2021); (Lahmiri and Bekiros, Mar. 2021)
8	8	(Bu and Cho, Nov. 2018); (Ponomarev et al., 2019); (Fior and Cagliero, Nov. 2020); (Peng and Lee, 2021); (Fiorini and Fiorini, 2021); (Zhang, Jul. 2021); (Sadewa, 2017); (Kamal et al., 2022)
8.25	**20**	(Gabrielsson and Johansson, 2015); (Zhang and Maringer, 2015); (Dash and Dash, Mar. 2016); (Mourelatos et al., Sep. 2018); (Zhu et al., Dec. 2018); (Azhikodan et al., 2019); (Attanasio et al., 2019); (Paiva et al., Jan. 2019); (Sarmento and Horta, Nov. 2020); (Tsai et al., 2020); (Wu et al., Oct. 2020); (Sun et al., Oct. 2020); (Tsantekidis and Tefas, 2020); (Makarov et al., 2021); (Kim, Aug. 2021); (Liu, Jan. 2022); (Nasirtafreshi, 2022); (Jaquart et al., Nov. 2022); (Gupta et al., 2022); (Murtza et al., 2022)
8.5	15	(Chu and Chan, 2018); (Hushani, 2019); (Rundo, Oct. 2019); (Lucarelli and Borrotti, May 2019); (Yuan et al., 2020); (Badr et al., 2020); (Weng et al., Aug. 2020); (Brim, Jan. 2020); (Betancourt and Chen, 2021); (Passalis et al., 2021); (Nalmpantis et al., 2021); (Hwang et al., Dec. 2023); (Xu and Zhang, Jun. 2023); (Ayitey Junior et al., 2022); (Zhang et al., 2023)
8.75	10	(Maratkhan et al., 2019); (Rundo et al., 2019); (Sattarov, et al., 2020); (Taroon et al., 2020); (Xu and Tan, Nov. 2020); (Chen and Huang, Nov. 2021); (Borrageiro et al., 2022); (Kuo et al., 2021); (Corletto et al., 2021); (Nan et al., 2022); (Chantarakasemchit and Nuchitprasitchai, 2021)
9	**20**	(Żbikowski, 2016); (Almahdi and Yang, Nov. 2017); (Shin et al., 2019); (Tsantekidis et al., Jul. 2021); (Conegundes and Pereira, Jul. 2020); (Park et al., Nov. 2020); (Aloud and Alkhamees, 2021); (Hirchoua et al., May 2021); (Lee et al., Aug. 2022); (Kang et al., 2022); (Song and Choi, 2023); (Xu, 2022); (Fjellstrom, 2022); (Banik et al., Mar. 2022); (Ortu et al., 2022); (Lee, 2022); (Sinha et al., 2022); (Ge et al., 2022); (Sarangi et al., 2020); (Sudimanto, 2021)
9.25	9	(Sezer et al., Jan. 2017); (Yang et al., 2020); (Khoa and Huynh, 2021); (Théate and Ernst, 2020); (Al-Ameer and Al-Sunni, Apr. 2021); (Shah et al., Apr. 2022); (Kwak et al., 2023); (Murtza et al., 2022); (Tsaih et al., 2018)
9.5	19	(Kim et al., 2019); (Sun et al., May 2019); (Lei et al., 2020); (Li et al., Dec. 2020); (Park and Lee, 2021); (Agarwal et al., May 2021); (AbdelKawy et al., Mar. 2021); (Ma et al., Aug. 2021); (Wang et al., 2022); (Felizardo, 2022); (Baltakys et al., 2023); (Liu et al., 2022); (Li and Qian, 2023); (Huang et al., 2023); (Xiang et al., 2022); (Peng and Lee, 2021); (Firouzi et al., 2021); (Firouzi et al., 2021); (Baasher and Fakhr, 2016)
9.75	5	(Yang et al., Dec. 2018); (Taghian et al., 2022); (Théate and Ernst, Jul. 2021); (Zhang et al., 2023); (Loh et al., 2022)
10	1	(Ta et al., Dec. 2018)

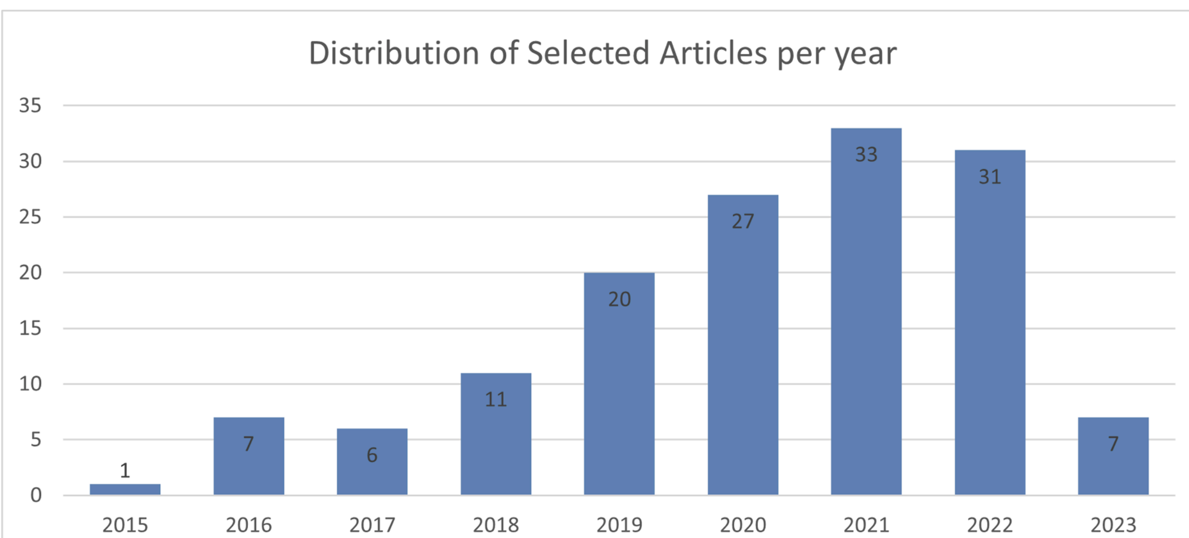

Fig. 21. Distribution of Selected Papers per Year.

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