IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 5 July 2023, accepted 26 July 2023, date of publication 31 July 2023, date of current version 7 August 2023.
Digital Object Identifier 10.1109/ACCESS.2023.3300036

SURVEY

Applications of Artificial Intelligence in the Economy, Including Applications in Stock Trading, Market Analysis, and Risk Management

AMIR MASOUD RAHMANI[1], BAHAREH REZAZADEH[2], MAJID HAGHPARAST[3], (Senior Member, IEEE), WEI-CHE CHANG[1], AND SHEN GUAN TING[1]
[1]Future Technology Research Center, National Yunlin University of Science and Technology, Douliou, Yunlin 64002, Taiwan
[2]Department of Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran 1477893855, Iran
[3]Faculty of Information Technology, University of Jyväskylä, 40014 Jyväskylä, Finland
Corresponding author: Majid Haghparast (majid.m.haghparast@jyu.fi)

This work was supported by the University of Jyväskylä (JYU) for Open Access.

ABSTRACT In an increasingly automated world, Artificial Intelligence (AI) promises to revolutionize how people work, consume, and develop their societies. Science and technology advancement has led humans to seek solutions to problems; however, AI-based technology is not novel and has a wide range of economic applications. This paper examines AI applications in economics, including stock trading, market analysis, and risk assessment. A comprehensive taxonomy is proposed to investigate AI applications in various scopes of the proposed categories. Furthermore, we will discuss this area's most significant AI-based techniques and evaluation criteria. As a final step, we will identify challenges, open issues, and future work suggestions.

INDEX TERMS Internet of Things, artificial intelligence, economy, machine learning, stock market, neural network.

I. INTRODUCTION

Artificial Intelligence (AI) is a rapidly evolving field with broad economic applications. AI technologies have become increasingly important for both the public and private sectors, providing invaluable insights into the current performance of the economy, as well as potential future directions. It can be used to develop and refine economic models, automate processes, and inform decision-making. AI is a broad term covering various technologies and techniques, but the core idea is that machines can be trained to "think" and make decisions. AI technologies can automate processes, provide insights, and conduct predictive analysis. AI is a rapidly developing field, and its economic applications are growing rapidly.

Recently, Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) techniques have gained significant traction in various sectors of the economy. AI-driven approaches have shown promising results for improving decision-making processes, optimizing strategies, and enhancing overall performance in stock trading, market analysis, and risk management. RL, a branch of AI, has become a powerful tool in portfolio construction, enabling automated decision-making processes and dynamic adaptation to market conditions [1]. By leveraging RL techniques, portfolio construction processes can benefit from adaptive and dynamic decision-making, improving risk-adjusted returns and enhancing portfolio performance [2]. Using RL for portfolio construction involves several steps. The first step in using RL for portfolio construction is defining a state representation that captures relevant market data, such as asset prices, trading volumes, and macroeconomic indicators [3]. Decision-making and policy learning are based on this state representation. RL algorithms require a defined action space, which specifies the possible actions each stage can take. An action space represents the allocation of funds across various assets in portfolio construction [4]. As another step, the reward function plays a crucial role in RL algorithms, quantifying the desirable of different actions. It may be built on risk-adjusted returns, volatility, or downside risk measures. Optimal decision-making policies through an iterative process of exploration and exploitation involve evaluating

The associate editor coordinating the review of this manuscript and approving it for publication was Jose Saldana.

different actions, updating the policy based on observed rewards, and gradually converging toward an optimal strategy [5]. It is the last step of RL utilization in portfolio construction, called policy learning.

AI can be used to identify patterns in complex economic data, allowing for more accurate predictions of future economic performance. It can also automate processes like financial transactions, improving efficiency, reducing costs, informing decision-making, improving economic model accuracy, and reducing decision-making time. Furthermore, complex economic changes and potential investment opportunities can be identified by posing AI.

AI has the potential to revolutionize the labor force through automation. Reducing labor through automation also reduces costs and increases efficiency since it allows higher-skilled workers to be employed.

Inflation has been a serious issue happening worldwide in recent years. The average per-capita income has not increased. However, people must still pay taxes and bills or buy houses. In these circumstances, people are likely to spend more than their earnings. As a result, people will seek various methods to increase their bank savings [6].

In finance, stock commerce provides such a chance to reach your goals. We probably did not have experience or knowledge of trading. We might buy stocks based on guesswork or luck. However, the point of investing is to prevent your asset from decreasing while increasing its value simultaneously. Fortunately, as time passed, experienced traders developed many analytical tools, such as elementary analysis, technical analysis, and measurement, which facilitated trading for investors or increased their investment success rate [7]. However, the tools developed using ML techniques have been used in computational sciences and various applications.

Experienced traders are attempting to implement ML to predict stock prices. However, every product has its characteristics, such as market liquidity and size. To solve this problem, modifying feature selection or data modeling might be the solution. Currently, AI assists investors with timely and precise suggestions for decision-making. However, the uncertainty of AI-based trading systems makes investors unwilling to rely on it. Thus, to reduce the risks, the main goal is to try combining multiple algorithms to gain more trust from the investors [8]. Currently, there are several ML models. However, two algorithms have outstanding performance: Long Short-Term Memory (LSTM) and Auto-Regressive Integrated Moving Average (ARIMA) [9]. A more sustainable and reliable model is possible with these two algorithms' collaboration.

At the time, AI is a rapidly evolving field with broad economic applications. AI technologies can automate processes, provide insights, and conduct predictive analysis. This paper will discuss AI's current and potential economic applications, its impacts on the labor force, and the potential for increased economic growth.

The paper is organized as follows: Section II describes the concepts and research methodology. The analysis of chosen papers in three main categories is provided in section III. Section IV answers the Research Questions (RQs) defined in Section II and proposes technical analysis and visual reports based on Section III findings. Several cases of AI applications in successful real-world companies are introduced in Section V, and Section VI concludes the paper.

II. CONCEPTS AND RESEARCH METHODOLOGY

As a foundational step, reviewing existing knowledge of a research scope provides researchers with a comprehensive understanding of the current state of research. Additionally, it assists them in identifying key theories, significant advancements, knowledge gaps, and unresolved questions, as well as exploring various perspectives, methodologies, and findings. Moreover, it enables researchers to assess the quality and credibility of previous research, ensuring that their review paper builds upon a robust foundation. Therefore, in this section, we analyze several recent review papers.

Cao et al. [10] reviewed modern economies focused on the smart version of Financial Technology (FinTech), which is empowered by Data Science and AI (DSAI). DSAI plays a critical role in transforming the economy, including businesses and personal finance, to be more intelligent and automated. Although the smart FinTech ecosystem contains technologies in vast various scopes, this study introduced some of them and focused on smart FinTech in financial businesses. This study reviewed DSAI techniques that empowered smart FinTech based on a comprehensive taxonomy, including complex systems methods, quantitative methods, data analytics, DL, privacy-preserving processing, augmentation, optimization, and to name a few provided in a table with their representative applications in smart FineTech. According to the study's authors, all FinTech areas have fundamental processes, such as design, production, operation, promotion, optimization, and safeguarding. The authors identified challenges and open issues from research analyzed in their paper and provided DSAI trends and future opportunities.

Shah et al. [11] investigated the ability of AI and ML to estimate stock prices, predict future trends, and manage portfolios. The authors compared the accuracy and error calculation of ARIMA, LSTM, Hybrid LSTM, Convolutional Neural Network (CNN), and Hybrid CNN techniques for stock price prediction to standard accuracy measures such as Root Mean Square Error (RMSE), MAPE, and MAE. A comparison of all the methods that have been evaluated has demonstrated that ARIMA is the worst prediction model. The LSTM and Hybrid LSTM models can be used to forecast future stock prices, while the NN and Hybrid CNN models, trained by large datasets, provide excellent stock trend forecasts. Therefore, a hybrid CNN/LSTM model is most accurate for predicting stocks' future trends and prices and can be used to build and manage portfolios. Stock fluctuations are also influenced by people's sentiments, which can

TABLE 1. A summary of relevant work on AI applications in the economy.

Reference	Review type	Main idea	Publication year	Publisher	Open issue	Taxonomy	Covered year
Cao et al. [10]	Overview	AI in smart FinTech	2021	Springer	✓	✓	Until 2021
Shah et al. [11]	Review	An accurate stock market forecasting model based on hybrid ML	2022	Elsevier	×	×	Until 2021
Mintarya et al. [12]	SLR	Stock market prediction by ML models	2023	Elsevier	✓	×	Until 2019

be observed on social media and analyzed using Natural Language Processing (NLP). Feeding sentiment analysis data into a Deep Neural Network (DNN) to predict stock trends and prices more accurately is possible. Even though this study introduced a properly integrated model for the stock market among its candidate models, many ML techniques may outperform these models and may be a direction for future studies.

Mintarya et al. [12] reviewed thirty research papers on ML methods for stock market prediction in a Systematic Literature Review (SLR) paper. These research papers used Neural Networks (NNs), Support Vector Machines (SVMs), LSTM, and other algorithms to predict stock market changes. According to the comparison, NN is the most frequently applied technique. This study is limited by a lack of taxonomy and a brief focus on a few papers.

Table 1 summarizes the main features of relevant review studies on AI applications in the economy and identifies their limitations. It facilitates the improvement of our research contributions.

Based on the previous research in this scope, the main contributions of this paper are:

- Introducing a comprehensive taxonomy of AI applications in the economy.
- Identifying the most significant AI-based techniques in the economy.
- Discovering the critical evaluation criteria in AI applications in the economy.
- Identifying the important challenges of AI applications in the economy.
- Providing open issues and future direction related to AI applications in the economy.

Determining key terminology can facilitate the understanding of subsequent content and provide clarity for readers. Therefore, we have defined and listed key expertise terms related to AI and economics to assist readers in the following:

- Investment strategy: It helps individual investors meet their financial and investment objectives.
- Portfolio value: The total monetary value of the assets held in your investment portfolio.
- Accumulated profit: The remaining profit corporations own after deducting dividend expenses.
- Volatility: It refers to the amount and speed at which prices change over time.
- Closing price: The latest price at which a stock is traded on a typical trading day.
- Efficiency: The time that the system comes up with the result.
- Accuracy: It assesses the classifier's ability to predict all classes properly.
- Absolute error: The discrepancy between a quantity's measured or perceived value and its true value.
- Autocorrelation: The degree of similarity between a particular time series and its lagged version over subsequent periods.
- Training performance: The result with the highest accuracy.
- Cumulative abnormal return: Cumulative returns of portfolio optimization strategies.

Based on the systematic review method, searching, refining, and choosing several studies are conducted and classified on AI economic applications. The keywords and search terms and their alternative synonyms we used to find relevant research papers are as follows:

(''AI'' OR ''artificial intelligence'') AND (''economy'' or ''finance'') AND (''prediction'' OR ''application'') AND (''stock'' OR ''market'' OR ''risk'').

After finding numerous papers based on our search terms, we applied several inclusion and exclusion criteria to effectively choose the most proper papers to refine our search results.

The inclusion criteria are as follows:

- Taxonomy categories and subcategories are included in the paper's title.
- Papers with high citations.
- Papers with a high scientific value.

The exclusion criteria are as follows:

- Papers published before 2017.
- Irrelevant papers.
- Papers without technical analysis.

Figure 1 shows the paper selection process.

Finally, the following figure illustrates the distribution of selected papers based on their publication year and publisher.

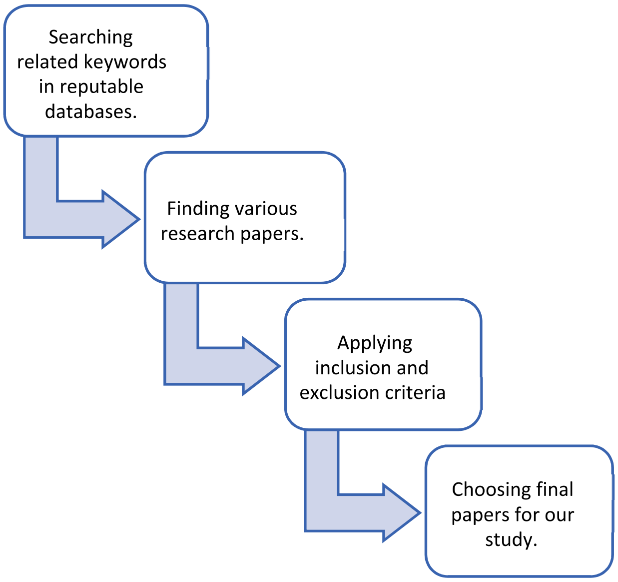

FIGURE 1. The paper section process.

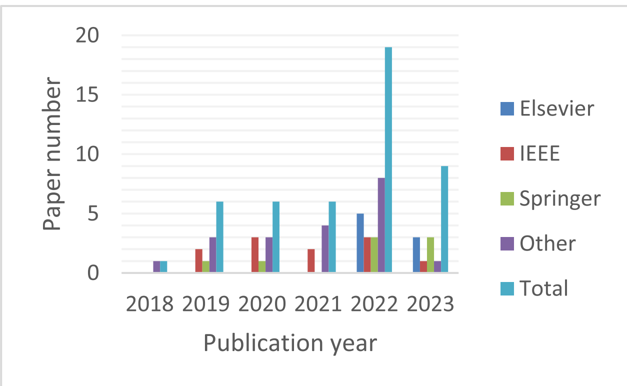

FIGURE 2. Year of publication and publisher of research papers.

Figure 2 illustrates the distribution of the selected research papers on AI applications in the economy from various reputable publishers such as IEEE, Springer, Elsevier, and other miscellaneous publishers.

This paper uses the systematic review method to address the following RQs:

- RQ1: Which branches of AI are applied in economics?
- RQ2: What are the challenges associated with AI applications in the economy?
- RQ3: Which techniques are most commonly used in AI applications in the economy?
- RQ4: What are the most significant evaluation metrics for AI applications in the economy?
- RQ5: What are the current open issues and future directions of AI in the economy?

Our analysis of AI applications in the economy is divided into three main categories: stock trading, market analysis, and risk management. In addition, the comprehensive taxonomy presented in Figure 3 details various applications of AI in each category.

ML algorithms are used in AI-based trading applications to analyze market data, detect trends, and predict potential buying and selling opportunities. AI algorithms can identify and interpret patterns in the market that may be too complex or subtle for humans to recognize [13]. A further benefit of AI is that it can predict stock price movements, detect market entry and exit points, suggest optimal portfolio allocations, automate the trading process, and allow traders to devote more time to research and analysis.

Market analysis can be conducted using AI to identify correlations between economic variables, such as consumer spending, market prices, and macroeconomic indicators. Through NLP, these applications analyze news articles, social media posts, and other sources to determine how people feel about a particular topic or company. It helps investors identify trends and determine public opinions [14]. As well as identifying trends, it can compare news sources.

Risk management entails identifying and mitigating risk factors through various measures. AI applications analyze large amounts of data to identify potential risks, predict outcomes, and provide timely insights for decision-making. This category includes different information, including financial information, market trends, and historical data [15]. By detecting anomalies, patterns, and correlations, AI algorithms can detect risks like fraud, cybersecurity threats, or operational inefficiencies. Through continuous data monitoring and analysis, AI systems facilitate proactive risk management, optimize portfolio risk exposure, and ensure regulatory compliance. Moreover, AI-based risk management solutions enable organizations to improve their response capabilities, prevent potential losses, and increase their resilience to rapidly changing risk environments [16].

III. SELECTED PAPERS ANALYSIS

According to the proposed taxonomy in Figure 3, we analyze the chosen papers in three main categories. First, we examine research on AI applications for stock trading, a hot topic in society today.

A. STOCK TRADING APPLICATIONS

People today attempt to increase their assets through various methods, including investing in stocks. Although investing in all products does not guarantee financial success, many people seek ways to predict stock prices. The fluctuating historical data due to the fluctuating price. As a result, economists are increasingly involved in developing models and methods for improving stock trading and forecasting market trends with greater accuracy [17]. The following is a review of some of these articles to identify the most common techniques and solutions, limitations, and challenges in this field.

Liang et al. [18] developed a hybrid wavelet-DL model that combines Daubechies wavelet (DB) with the bidirectional LSTM (BLSTM) model called (DB-BLSTM) to cope

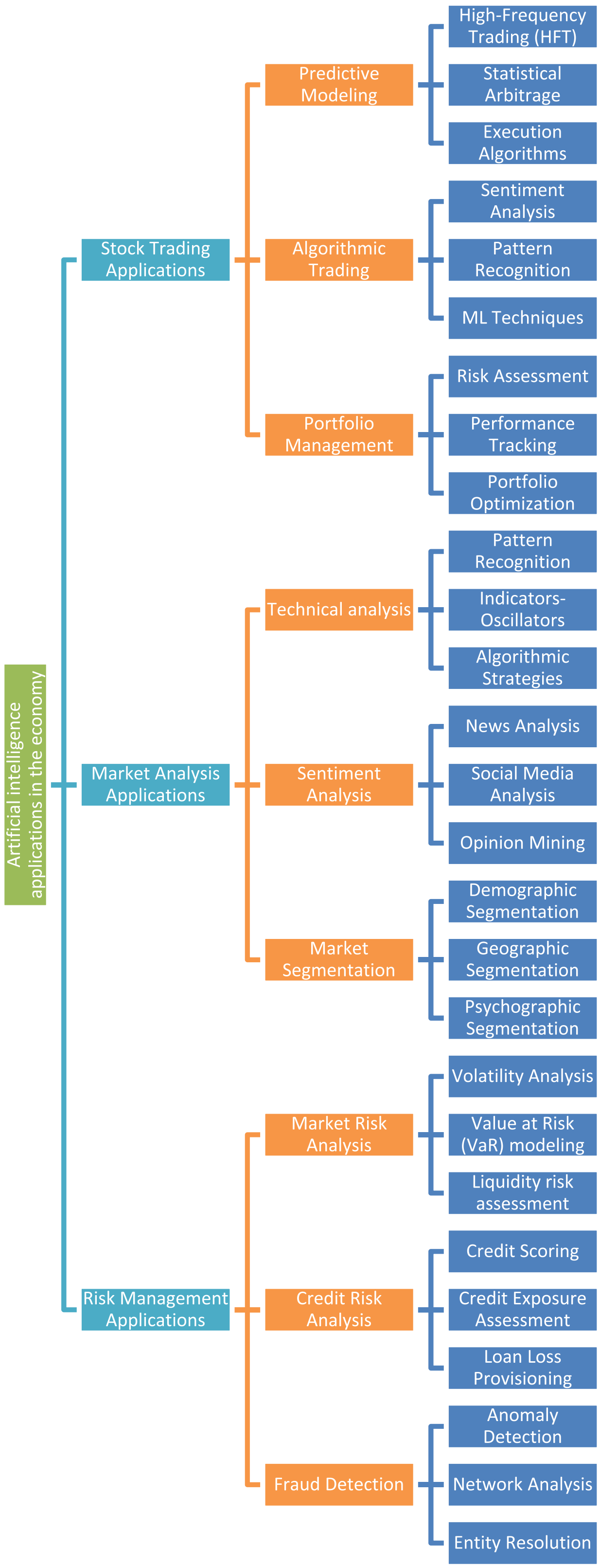

FIGURE 3. **The taxonomy of AI applications used in the economy.**

with complicated periodicity and nonlinearity features in the high-frequency data and analyze high-frequency stock index futures data in developing markets. Wavelets are utilized for their ability to reduce the interference caused by high-frequency data and their sensitivity to time-varying frequencies. Moreover, the researchers constructed trading strategies based on the proposed hybrid prediction models and evaluated the results regarding realized returns, Sharpe ratios (SRs), and maximum drawdowns. After deducting transaction costs and benchmark returns, the strategies generate significant excess returns ranging from 15.69% to 45.52%. The strategy also exhibits an impressive SR, indicating favorable risk-adjusted returns. The proposed model is compared with commonly used models like LSTM and Artificial Neural Networks (ANN) for predicting stock index futures intraday trends. The empirical comparison results demonstrate superior performance in both in-sample and out-of-sample tests. However, the lack of an international dataset for evaluating this model's effectiveness limits this study which is a potential direction for future research.

Cohen [19] developed algorithmic trading platforms for popular cryptocurrencies using ML systems based on the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Keltner Channels trading oscillators. The LSTM is used to identify optimal trading setups and generate trading signals for automated intraday trading of Bitcoin, Ethereum, Binance Coin, Cardano, and XRP across various timeframes, ranging from 5 to 180 minutes. The system alternates 5, 15, 30-, 60-, 120-, and 180-minute timeframes between trading bars to maximize profits. Comparing these three strategies, the RSI system outperformed the Buy and Hold (B&H) strategy for all five cryptocurrencies, which supports its effectiveness in improving trading outcomes under both uptrends and downtrends. In particular, when trades were split into long and short positions, the RSI-based system consistently performed better in long positions, whereas the other systems generated adverse Net Profit (NP) for Ethereum and Cardano. According to the results of this study, longer time frames, such as 60 and 120 minutes, offered better trading results than shorter time frames, such as 5 and 15 minutes. A study concluded that intraday algorithmic trading systems could be more profitable for cryptocurrencies and suggested the development of similar systems in the future based on other AI methods.

Technology has accelerated the development of many emerging industries in China, resulting in continuous growth and progress in the nation's economy. Still, it has also led to severe turbulence in the stock market, making predicting stock prices complex and difficult. Therefore, Kan et al. [20] proposed a dynamic portfolio management model that combines Deep Reinforcement Learning (DRL) and stock trading to improve stock prediction. Various AI techniques were used in their model, and the Shanghai Stock Exchange dataset was used to simulate it. Based on SR and Accumulated Portfolio Value (APV) evaluation metrics, this model outperforms its competitors. This model did not consider transaction costs, an area for future study.

Kumar et al. [21] developed an LSTM-based stock price prediction model that improves prediction accuracy and performance over various timeframes. Mini-batch gradient descent is used as the optimization algorithm in this model to enhance speed and reduce prediction errors. The authors simulated their proposed model in Python using datasets from the Pandas website to compare its accuracy with other DL models. Results show that this model performs better than previous models, speeding up prediction times and reducing errors. A lack of measurement of various evaluation metrics limited this study, which may form a direction for future research.

Zhao et al. [22] focussed on the complexity of financial markets because of the variety of industries, investors, and data types to be considered. In this study, they investigated the development of agent systems for everyday stock trading decision support, and they proposed an improved deep Q-learning algorithm model for stock trading prediction to deal with divide-and-conquer problems in an integrated environment. The authors combined Q-learning agents and Median Absolute Deviation (MAD) algorithms to efficiently divide and conquer stock trading problems in an integrated environment. This combination enables stock data processing from the starting point and analyzing them based on their characteristics which is an essential foundation for future agent simulation by the Q-learning model. This combined predictive model covers the challenges of single Q-learning methods, including original data preprocessing, reward values, and model testing problems. Under big data, this model uses RL methods to forecast changes in stock trading. MAD is used to analyze univariate numerical data when high correlations or sample bias are an issue due to its greater adaptability to outliers than the standard deviation.

Further, it solves the problem of high correlation between data and optimizes the State, Action, and Reward functions, making it suitable for use in financial markets. Using the NASDAQ Composite (IXIC) simulator, "^IXIC," and a real dataset of the US stock market, the authors demonstrated that their proposed approach outperformed the separate Q-learning framework. Additionally, the Q-learning convergence analysis is evaluated in this study. As a result of the evaluation, this model outperformed a single Q-learning approach and is highly effective for simulating and predicting stock trading in 2020. This study examines only the theoretical aspects of stock market prediction, while on the practice side, traditional econometric models are combined with RL models that decrease prediction accuracy. The present model can be further developed by incorporating other potential ML models to inform investment decisions, forecast stock prices, and create trading strategies in the real market.

Lee et al. [23] proposed a stock price prediction model using LSTM and explored TWSE 0050, the most traded ETF on Taiwan's stock exchange, as a case study. This research's dataset is the period between Jan 2019 and Oct 2019. Using LSTM and available data from the Taiwan Stock Exchange may attest to the feasibility of utilizing a DNN to experiment. The results show 75% accuracy. Enhancing accuracy and utilizing more indicators, such as chip analysis, financing, and securities lending, in this model is a direction for future work.

Kumar et al. [24] proposed a hybrid CNN-LSTM stock price prediction model to enhance the efficiency and correctness of stock prediction. They use historical data based on the NIFTY50 index. The period of this dataset is between 2015 and 2020. They tried various prebuilt and DL models to predict the value of the stock in the next ten days. They initially attempted to combine the ARIMA and the Seasonal ARIMA model with exogenous components (SARIMAX). They discovered this technique had lower accuracy than the method combined with CNN and LSTM. As a result, using the same dataset, the new model, which combines CNN and LSTM, has the best performance. The future work of this research is to enhance the correctness by applying the RL method and a larger dataset.

Selvamuthu et al. [25] predicted the stock price using three distinct algorithms. The algorithms are Levenberg-Marquardt, Scaled Conjugate Gradient (SCG), and Bayesian Regularization. They take data from Indian companies and use the 15-minute data to analyze it with the three algorithms. Finally, they compared the results of the three algorithms. The results indicate that these algorithms have an accuracy of up to 99.9%. However, the accuracy after fifteen minutes decreased to 96.2%, 97.0%, and 98.9%, respectively. Although the accuracy of these three algorithms has reduced, as evidenced by this study, the result calculated by the SCG algorithm has the best performance. This research aims to increase the accuracy of the prediction and allow users to predict specific periods from historical data to get a better result.

Ta et al. [26] researched several core components of the quantitative trading system. They discovered that ML has many advantages compared to traditional algorithmic trading. Using ML, you may synchronously apply certain trading strategies and adapt them based on the real-time market. Besides, combining numerous optimized algorithms can control risks during every transaction. It might be an ideal situation in a real-time market, but their model can execute effectively after backtesting. The two models both have the characteristics of high accuracy and return. Also, the models have better revenue compared to the S&P 500 ETF-SPY.

Farahani and Hajiagha [27] used ANN to predict stock prices and trained their model by Social Spider Optimization (SSO) and Bat Algorithm (BA), which are called metaheuristic algorithms. Then, they used the Genetic Algorithm (GA) to select features and choose the best and most relevant indications based on the input's technical characteristics. They chose the loss function as the evaluation standard to measure the model's accuracy. In addition, they applied a time series method to forecast the stock price and compared it to the model that included ANN-metaheuristic techniques. Finally, they selected indicators like the S&P 500, DAX, and FTSE 100 as their targets.

Sanboon et al. [28] proposed a long-term stock price prediction model using LSTM. They observed that stock price forecasting is one of the unachievable tasks in the current era. Also, current forecasting methods cannot predict a stock's long-term price. Therefore, they cannot consider the relationship between the prior price and the future price; hence this research has created a model capable of capturing long-term stock price correlations. The accuracy of the suggested model was evaluated on five equities between January 2015 and December 2017, and the results were compared. The experimental results show that the suggested model outperforms all competing models.

Safari and Ghavifekr [29] proposed an AI-NN price prediction model tunned by Python with a security shell that supports cryptocurrencies. This system can retain a copy of the final data in the user's configuration email. Additionally, it can predict the price of cryptocurrencies like Bitcoin (BTC) and Ethereum (ETH). They evaluated their idea and proved its outperformance. The advantage of this system is that it can be extended to other applications, like education, as a future work.

Chacón et al. [30] suggested a method for enhancing the predictability of financial time series by employing a full ensemble empirical modal decomposition with adaptive noise and intrinsic sample entropy. They utilized their methodology on the S&P 500 index stocks from January 2018 to April 2020 to evaluate the integrated model. They trained his LSTM model for each stock's closing price in the time series to predict the next closing price. The results reveal a relationship between the entropy of the decomposed signal and the prediction accuracy performance, which is seen in the decomposed signal when the short-term complexity of the financial time series is minimal compared to the series energy. It suggests a higher predictive ability after removing the signal entropy. The highest frequency is greatly improved. Moreover, the results show a 31% enhancement in stock price direction prediction using the traditional LSTM architecture.

Carta et al. [31] proposed an ML method to address a binary classification problem that aims to foresee the magnitude of the future stock price of businesses in the S&P 500 index. A lexicon set is generated from articles published worldwide to identify the most influential words in the market within a specific time interval and economic sector. A feature engineering process is then performed from the generated lexicon, and the resulting features are fed to a decision tree classifier. A forecasted label (high or low) indicates whether the target company's price will go over or below a specified threshold the next day. Evaluations of performance utilizing a walk-forward technique and a strong baseline indicate that their approach greatly exceeds that of their opponents. In addition, the established AI technique is explicable in that it analyzes the "white box" behind the classifier and gives a set of reasons for the findings achieved. The authors used Python to develop their framework and applied a decision tree classifier for the model training. They compared this model to the existing models and proved its high accuracy and outperformance. The readability of the results of this model by humans, integrating semantic features to it, and using NN for its development are directions for future work.

Ghosh et al. [32] provided a framework to compare the stock price before and after COVID-19. This model can extract the characteristics of stocks, such as historical volatility, sectoral outlook, and market sentiment. The explanatory features are screened using the suggested Ensemble Feature Selection (EFS) approach, which combines the Boruta and Regularized Random Forest (RRF) algorithms. For predicting, Regularized Greedy Forest (RGF) and DNN, two cutting-edge AI methods, are combined with Kernel Principal Component Analysis (KPCA) and Autoencoder (AE). The results indicate that the proportionate importance of the explanatory elements in futures price forecasting changes depending on the company and period under examination.

Liu et al. [33] proposed a technique for stock ranking forecasting by combining the Temporal Convolutional Network (TCN) with a Channel-Time dual Attention Module (CTAM) to improve the capability to manage dependencies within series. Stock industry features were also considered by creating an industry-stock Pearson correlation formula and producing a vector that completely describes stock industry qualities using a matrix factorization algorithm. The effectiveness of the proposed technique was demonstrated through experiments on three datasets. The Investment Return Ratio (IRR) and SR were calculated based on the technique's prediction on the datasets.

Jang and Seong [3] created a deep RL portfolio optimization approach incorporating DL and modern portfolio theory. They addressed the multimodal problem using Tucker decomposition and technical analysis as inputs. Their method surpassed cutting-edge algorithms regarding the SR, annualized return, and maximum drawdown.

Lee et al. [34] believed that the strong foundation of the stock market could positively affect the whole economy. As a result, they utilized DL and Technical Index to predict the movement of the stock in an abbreviated period. In this paper, they select TWSE 0050 as their subject, the largest ETF trading volume in Taiwan's stock exchange. By using opening price, closing price, and other technical indexes, including KD, RSI, and BIAS, it can construct LSTM models and train them. As the outcomes show, the model's accuracy is 83.6%.

Peng et al. [35] examined the relationship between AI-based Financial Management (FM) and Mineral Resource Management (MRM) in the US economy from 1980-2020. The findings suggested an asymmetric correlation between FM and Mineral Resource Rent (MRR). Positive shocks of FM were negatively related to MRR, while negative shocks were positively correlated. This work aims to implement AI-based financial systems in the mining industry to improve

MRM and assure worker performance and comfort, leading to longer growth.

Tang et al. [36] proposed News Distilling Network (NDN) prediction model using NL and collaborative filtering to facilitate similarity measurements. They combined news selection mechanisms with NNL architecture to identify the linkage between stocks and news. They used real-world data to prove their framework's efficiency.

Vicente et al. [37] proposed an RL market agents application to simulate an intelligent stock market. They examined the market maker's approach from an agent-based viewpoint. This study analyzes the proposed application's performance in non-competitive and competitive situations. They also examined their strategy through various experiments and described the impact of competitive environments on RL agents' performance. They demonstrated that RL and DRL techniques are profitable market-making methods, allowing people to understand their stock market behavior better. Previous studies on financial news mainly refer to news coverage of the target financial instruments, which may be affected by sparse data.

Day and Lin [38] designed a robo-advisor using several ML algorithms and DL prediction techniques. The advisor can assist the user in making decisions by optimizing the investment portfolio. This research integrates various techniques, including ML, data analysis, and investment portfolio optimization. In that case, they hoped they could predict the trend without using historical data or the investors' perspectives. Finally, they chose the algorithms with the highest accuracy, and the result shows that the Return on Investment (RoI) is 12% annually. As for future work, they can try adding more technical indicators to train their model to extract the most decisive characteristics and enhance their model.

Xu and Tan [39] suggested that a risk-diversified, market-neutral, and dynamic portfolio management model deal with systematic risk in portfolio management. They used matching trading methods, deep RL, and standard portfolio management models to make this approach work. Their experiments on 32 stocks in the Chinese A-share market show that the pairing-based deep portfolio model has the advantage of weighing investment returns and risks in dynamic portfolio management problems.

Chhajer et al. [40] presented a study that provided an overview of using ML and AI as predictive analytics tools for stock market forecasting. They reviewed the advantages and disadvantages of ML in this subject and the benefits and drawbacks of using modern technologies for this goal. The study also focuses on the applicability of three distinct ML technologies for stock market forecasting, namely ANNs, SVMs, and LSTMs. The study emphasized the importance of utilizing these technologies to make calculated predictions and invest safely in the turbulent stock market.

Illa et al. [41] applied AI techniques to evaluate the information submitted to stock exchanges and developed new techniques to predict equity costs and limit exposure to interest on financial exchanges. Materials from reports and other important resources use regular linguistic processing and assembly learning methods called random forest models and SVM. The problem of predictability of storage costs is known as the problem of characterization to make better decisions.

This paper presents a comparison table summarizing the main features of research conducted in this area, including the main context, applied techniques, evaluation methods, evaluation metrics, benefits, limitations, and future work. We aim to reach valuable results for future studies using the technical and statistical interpretations resulting from comparing these factors.

A summary of the most significant features covered in the analyzed papers in this category is presented in Table 2.

The following results are based on the interpretation from comparing the analyzed papers in this section.

Overarching themes

- Application of DL and NN

Designing trading strategies and predicting stock prices based on DL and NN architectures such as LSTM, CNN, and hybrid models.

- Integration of RL

Incorporating RL algorithms, such as Q-learning, with portfolio management and stock trading strategies.

- Predictive Models and Hybrid Approaches

Enhancing the accuracy of stock price prediction by incorporating AI techniques, such as wavelet analysis, sentiment analysis, technical indicators, and social media data.

Emerging trends

- Integrating alternative data sources

Utilizing non-traditional data sources to supplement historical data, such as news sentiment, social media, and domain-specific terminology.

- Short-term and long-term predictions

Long-term and short-term stock price predictions using LSTM.

- Explainable AI in stock trading

Understanding the reasoning behind trading decisions and developing interpretable models.

Critical gap

- Real-time trading strategies

Real-time trading strategies by considering market conditions' rapid changes.

- Generalization of models

Developing AI models to generalize across a variety of financial markets.

- Model evaluation and robustness

Robustness and reliability of AI-based trading models.

Based on the analysis of the future work column content in Table 2, improving the accuracy of forecasting stock trading is one of the main concerns in using AI in this area. In most of these papers, developing the proposed prediction models is suggested in different ways, including using

TABLE 2. Selected articles of stock trading applications category.

Research	Main context	Applied technique	Evaluation method	Evaluation metric	Benefit	Limitation	Future work
Liang et al. [18]	Analysis of high-frequency stock index futures data using a hybrid wavelet-DL (DB-BLSTM) model	-DL	-Simulation -Dataset	-MSE[1] -Goodness of fit (R^2) -DA[2] -Robustness	-Enabling policymakers to stabilize market prices -Improving intraday quantitative trading strategies -Excellent excess returns -Risk compensation return	-Lack of dataset variation	The evaluation of the proposed model's effectiveness using international datasets
Cohen [19]	Algorithmic trading systems for popular cryptocurrencies using oscillators	-LSTM -SVM	-Simulation -Dataset	-NP -PF[3] -PP[4]	-Maximizing profits	-	-Developing other ML techniques -Improving profit
Kan et al. [20]	The combination of DRL and trading strategy in portfolio management	-DRL -CNN -LSTM	-Simulation -Dataset (Shanghai Stock Exchange)	-APV -SR	-Trade-off between risk and investment returns -High performance	-Not considering transaction cost	-Adding transaction costs to dynamic portfolio management
Kumar et al. [21]	Stock price prediction model by LSTM	-LSTM -ML (Mini-batch gradient descent)	-Simulation (Python) -Dataset (Pandas data reader website)	-Accuracy	-Increasing profit -Accuracy -Increasing speed -Reducing error	-Insufficient evaluation criteria	-Using various evaluation metrics
Zhao et al. [22]	Combination of AMD and Q-learning to build a stock trading model	-Q-learning -RL	-Simulation -Dataset (US stock market- IXIC)	-Performance	-Improving performance	-Not practical	-Designing in the more complex network -Optimizing prediction

[1] Mean Squared Error (MSE)
[2] Directional Accuracy (DA)
[3] Profit Factor (PF)
[4] Percent of Profitable (PP) trade

diverse AI methodologies, utilizing a variety of big data, and applying additional evaluation criteria. A strong correlation exists between these future study directions, which implies improving market predictions' accuracy and validity. A further indication that accuracy is a critical aspect of stock trading is the frequent assessment of this metric in more than half of the analyzed papers in this category, as shown in Table 3. Consequently, it can be concluded that extending AI applications to financial applications requires an increasing level of correctness and validity of market volatility predictions. The second key point worth mentioning is the lack of various evaluation criteria for assessing the proposed novel findings in this area of research. This comparison and analysis demonstrate that the lack of consideration of different evaluation criteria is one of the significant limitations of this study on AI applications in stock training.

According to the evaluation metrics in the previous table, several metrics measure the same factors. These metrics may be relevant and important depending on the specific context and objectives of the AI-based stock trading system in the described papers. The following table presents the evaluation frequency of various criteria in several extensive groups. Based on their repetition, we can find the most critical measures in AI-based stock trading.

- Accuracy

It refers to the correctness or precision of predictions made by an AI-based stock trading model. Precision, recall, and F1-score are commonly used in classification tasks and assessed for binary prediction accuracy. They can be useful in classifying stock market movements or identifying trading signals.

- Performance

While "performance" is a broad term, it encompasses various metrics that evaluate trading strategy effectiveness. Metrics such as R2, DA, PF, APV, SR, SAM, RSI, BIAS, Williams%R, MACD, R, MAE, and MAPE can be considered

TABLE 2. ***(Continued.)*** **Selected articles of stock trading applications category.**

Lee et al. [23]	Short-term prediction of stock price movements using the DNN and technical indicators	-LSTM -RNN[1] -DNN	-Simulation -Dataset (TWSE 0050)	-Accuracy -SAM[2] -RSI -RSV -BIAS[3] -Williams%R[4] -MACD	-Feasibility -Effectiveness	-Not considering business factors	-Improving accuracy -Applying more technical indicators -Chip analysis
Kumar et al. [24]	Stock price prediction using a hybrid CNN-LSTM model based on historical data and social media	-CNN -LSTM -ARIMA -SARIMAX	-Implementation (Google Colab) -Simulation (Python) -Dataset(NIFTY50, Twitter textual data)	-RMSE	-Probability -Autocorrelation -Performance -RMSE	-Using a short-period dataset	-Enlarging dataset -Applying RL -Data retraining -Quantization model to int8
Selvamuthu et al. [25]	Pattern recognition and stock prediction based on three NN learning algorithms	-SVM -ANN -BPNN[5] -NN[6] -Levenberg-Marquardt -Scaled Conjugate Gradient -Bayesian Regularization -SCG	-Simulation -Dataset (tick)	-Accuracy -MSE -MPE	-Accuracy -Performance	-Neglecting sentiment analysis	-Considering sentiment analysis -Using RNN
Ta et al. [26]	Quantitative prediction and portfolio optimization using ML	-Linear regression -SVR -LSTM -Decision tree -RF[7] -Wrapper	-Simulation -Dataset	-Accuracy -MSE -SR -R[8]	-High accuracy	-False-positive	-Backtesting
Shahvaroughi Farahani and Razavi Hajiagha [27]	Hybrid ANN-metaheuristic and time series models for stock prediction	-ANN -SSO -BA[9] -GA -ARMA -ARIMA	-Simulation -Dataset	-MAE -MSE -R^2	-High accuracy -Low testing error -High validation -High-speed --Reducing model complexity -Robustness	-Local optima trap	-Using different meta-heuristic algorithms in this model
Sanboon et al. [28]	Stock price long-term prediction using LSTM	-LSTM -SVM -Multilayer perceptron -LR[10] -K-nearest neighbors	-Implementation (Yahoo Finance API) -Dataset (2015-2017)	-Performance -Accuracy	High Accuracy	-Lack of various evaluation factors	-Considering the exchange rate -Using technical indicators
Safari and Ghavifekr [29]	An AI-NN price prediction model considering security	-AI -ANN	-Dataset -Simulation (Python)	-RMSE	-High ability like sending data to user email -Generating Excel file -High accuracy -Security	-Not considering various evaluation metrics	-Extending to various applications like education
Chacón et al. [30]	Improving the accuracy of	-RNN -Ensemble Empirical	- Dataset -Simulation	-MAPE -WAPE	-Independence -High accuracy		-Reducing sequential

[1] Recurrent Neural Network (RNN)
[2] Simple Moving Average (SAM)
[3] Bias Ratio (BIAS)
[4] William's Oscillator (Williams%R)
[5] Back Propagation Neural Network (BPNN)
[6] Neural Network (NN)
[7] Random Forest (RF)
[8] Return portfolio (R)
[9] Bat Algorithm (BA)
[10] Logistic Regression (LR)

TABLE 2. ***(Continued.)*** **Selected articles of stock trading applications category.**

	financial time series prediction	Mode Decomposition -LSTM -SampEn		-DA[1] -ARV[2] -TheilsU	-High correct prediction rate		data complexity -Enhancing predictability
Carta et al. [31]	Using news and domain-specific terminology to forecast the stock market	-AI -Decision tree -Walk-forward technique	-Simulation (Python) -Dataset	-Accuracy -Precision -Recall -F1-score	-Extendability -High Accuracy	-Not readable results by humans	-Integrating semantic features -Using NN
Ghosh et al. [32]	Hybrid AI-based stock price forecasting framework	-EFS[3] -RGF[4] -DNN -KPCA[5]	-Simulation (Python) -Dataset	-IA[6] -TI[7] -DPA[8] -NSE[9]	-High performance	-	-Applying the proposed framework to various companies
Liu et al. [33]	Stock trading predictive modeling	-TCN - CTAM -Matrix factorization algorithm	-Dataset (constituent stock's data)	-SR -IRR	-Effectiveness	-	Using Ticks data
Jang and Seong [3]	Portfolio optimization approach combining DRL with modern portfolio theory.	-DRL -Tucker theory	-Dataset (2008-2019)	-SR -Annualized return -MDD[10] -APV	-Solving the multimodal problem -Dynamicity	-Lack of technical analysis	-Applying technical analysis -Using RL -Adjusting stable reward function
Lee et al. [34]	Technical analysis and DNN for Taiwan's stock price movement prediction	-LSTM -DNN	-Simulation -Dataset	-Accuracy	-Feasibility -Effectiveness	-Not considering business factors	-Improving accuracy -Applying more technical indicators -Chip analysis
Peng et al. [35]	The link between AI-based FM[11] and MRM[12] in the US Economy	-ADF[13] -PP[14] -KPSS[15] -BDS testing -NARDL[16]	-Dataset (1980-2020) -Implementation	-MRR[17] -GDPPC[18] -EU[19] -Trade	-Developing efficiency -Reducing mismanagement	-Lack of risk management calculation	-Improving efficiency

[1] Direction Accuracy (DA)
[2] Average Relative Variance (ARV)
[3] Ensemble Feature Selection (EFS)
[4] Regularized Greedy Forest (RGF)
[5] Kernel Principal Component Analysis (KPCA)
[6] Index of Agreement (IA)
[7] Theil Index (TI)
[8] Directional Predictive Accuracy (DA)
[9] Nash-Sutcliffe Efficiency (NSE)
[10] Maximum DrawDown (MDD)
[11] Financial Management (FM)
[12] Mineral Resource Management (MRM)
[13] Augmented Dickey-Fuller (ADF)
[14] Phillips-Perron (PP)
[15] Kwiatkowski–Phillips–Schmidt–Shin (KPSS)
[16] Non-linear Autoregressive Distributed Lag (NARDL)
[17] Mineral Resource Rent (MRR)
[18] Gross Domestic Product Per Capita (GDPPC)
[19] Energy Consumption (EU)

performance metrics as they assess different aspects of a trading model's effectiveness.

- Risk Management

Metrics such as robustness, MDD, IA, TI, and NSE are indicators of risk management and a trading strategy's ability to withstand adverse market conditions.

- Investment-related metrics

Metrics like NP, PP, ARV, TheilsU, DPA, and IRR focus on measuring financial gains or returns generated by a trading strategy.

According to the table above, accuracy and performance are equally important and more significant than the other

TABLE 3. The evaluation factors for stock trading applications category.

Research	Accuracy	Performance	Risk assessment metric	Investment-related metric
Liang et al. [18]	✓	✓	✓	
Cohen [19]			✓	
Kan et al. [20]		✓		
Kumar et al. [21]	✓			
Zhao et al. [22]		✓		
Lee et al. [23]	✓	✓		
Kumar et al. [24]	✓			
Selvamuthu et al. [25]	✓	✓		
Ta et al. [26]	✓	✓		
Shahvaroughi Farahani and Razavi Hajiagha [27]	✓	✓		
Sanboon et al. [28]	✓	✓		
Safari and Ghavifekr [29]	✓			
Chacón et al. [30]	✓	✓		✓
Carta et al. [31]	✓			
Ghosh et al. [32]			✓	✓
Liu et al. [33]		✓		✓
Jang and Seong [3]		✓	✓	
Lee et al. [34]	✓	✓		
Peng et al. [35]			✓	
Total	12	12	5	3

dimensions of stock trading. In light of AI-based stock trading, which predicts and optimizes stock price fluctuations in an automated manner, the accuracy and performance of intelligent models are crucial evaluation factors.

B. MARKET ANALYSIS APPLICATIONS

In this subsection, we analyze the application of AI in market analysis in three subcategories, including technical analysis, sentiment analysis, and market segmentation; each has several subcategories.

As a paper that focused on oscillators in the technical analysis subcategory of market analysis applications, Lee [42] proposed an innovative Chaotic Type-2 Transient-Fuzzy Deep Neuro-Oscillatory Network (CT2TFDNN) system for long-term financial prediction in worldwide investment. The CT2TFDNN extends the author's original work on the chaotic discrete-time neural oscillator with deep transient-chaotic features, the Lee oscillator. An effective representation of an IT2FLS with a chaotic transient-fuzzy club function, effective time-collection community schooling, and forecasting of the usage of a chaotic deep neuro-oscillatory community with retrograde signaling. CT2TFDNN no longer offers a rapid, chaotic fuzzy-neuro deep studying and predicting result but also effectively determines the huge facts overtraining and impasse problems, which might be normally imposed using conventional Recurrent Neural Networks (RNN) with the use of classical sigmoid-primarily based activation functions. CT2TFDNN comprises 2048 trading-day time-collection monetary data and the top-10 fundamental monetary indicators as fuzzy monetary indicators for the real-time prediction of 129 global monetary products, including nine fundamental cryptocurrencies, 84 global currencies, 19 fundamental commodities, and 17 global monetary indices.

Khashman and Carstea [43] described a powerful, supervised NN-based oil price prediction system. The West Texas Intermediate (WTI) dataset of crude oil prices spanning 24 years provides the NN with new critical economic and seasonal factors as input. The model has a five-dollar-per-barrel accuracy limit for its weekly oil price predictions. The experimental findings show that the achieved right prediction rate of 88% is greater than rates reported in other relevant research. The authors suggested that NNs may be better at predicting oil prices.

Al-Fattah [44] introduced a novel model for predicting the price of gasoline. This model uses AI, GA, ANN, and data mining techniques to predict the gasoline price. It monitors and documents the price fluctuations of gasoline. The result shows that the prediction matches the historical data. In addition to explaining the behavior and capturing the dynamics of oil-price volatility, the model demonstrated the ability to predict the direction of changes in oil market volatility with an accuracy of 88%.

Vekaria et al. [8] proposed an economy prediction scheme that combines AI, Big Data Analytics (BDA), and the Internet of Things (IoT) to promote economy-boosting activities called ξ boost. The scheme uses LSTM for early economic prediction, particularly in the case of the COVID-19 pandemic in India. The authors evaluated the prediction accuracy of their scheme using Python and different economic datasets. They also compared it to other existing models based on MAPE and RMSE. Results showed that their scheme performed exceptionally well in predicting the economy and could be applied to other countries for future research.

Alonso de Armiño et al. [45] proposed a hybrid AI system to examine how economic factors and transportation patterns interact. The temporal patterns of road traffic and macroeconomic developments are studied using supervised and unsupervised NNs and clustering algorithms. The suggested approach is validated by connecting Spanish road transportation data and macroeconomic changes over six

TABLE 4. Selected articles of market analysis applications category.

Research	Main context	Applied technique	Evaluation method	Evaluation metric	Benefit	Limitation	Future work
Lee [42]	System for long-term AI-based financial prediction	-Fuzzy logic -DNN -GA	-Simulation (MATLAB) -Dataset	-RMSE -DFPE[1]	-Solving massive data overtraining -Deadlock resolution -Real-time -Reducing complexity -Improving training speed	-	-Data mining of big data -Using neural RS techniques -Agent-based trading -Integrating with QPL[2]
Khashman and Carstea [43]	Oil-prediction system based on supervised NN	-NN	-Simulation -Dataset	-Accuracy	-High accuracy	-Lack of comprehensive comparison	_Using different AI techniques
Al-Fattah [44]	Hybrid oil price prediction model based on different AI algorithms	-GA -ANN -Data mining -Time-series	-Simulation -Dataset	-Accuracy -Performance -SR -Recall -MRP[3] -MSP[4] -RMS[5]	-Dynamicity -High accuracy	-	-Increasing predictability -Improving accuracy
Vekaria et al. [8]	AI-based data analysis for covid-19 prediction and economic growth	-LSTM -BDA -ML -IoT	-Simulation (Python) -Dataset	-Accuracy -MAPE[6] -RMSE	-High accuracy	-Not considering population density	-Apply to other countries
Alonso de Armiño et al. [45]	Transportation patterns and the economy through NN and clustering	-NN -Clustering -TSP[7] -EPP[8] -K-means -Agglomerative	-Dataset -Implementation	-MSE -Accuracy	-High accuracy	-Not scalable	-Scaling
Coulter [46]	Using NLP to discover the news's effect and the market's price movements.	-NLP -Text analysis	-Dataset -Simulation (Python)	-Coherence score	-Identifying important factors in media which affect the market	-Not assessing various evaluation metrics	Enhancing Crypto discourses models Identifying discourse and news sources correlation
Koch et al. [47]	Sentiment analysis of news	-Textual analysis -Sentiment analysis	-Dataset -Implementation	-Sentiment score -Accuracy	-Data standardization -Considering various features of news	-Not differentiation between positive and negative sentiments of news	Evaluating sentiment spillover
Caporale et al. [48]	News sentiments and portfolio flow linkage.	-DPD[9] model	-Dataset -Implementation	-Lagged dependent variables	-Considering various assessment metrics	-Lack of simulation environment	-Investigating the asymmetries in the effects of news on business expansion and recession
Barbaglia et al. [49]	Forecasting model based on sentiment analysis of economic news	-ML -LDA[10] -Clustering	-Dataset -Simulation	-Sentiment score -GDPC1 -INDPRO[11] -CPIAUCSL[12]	-Considering macroeconomic factors	-Lack of simulation environment	Text analysis application in economy

[1] Daily Forecast Percentage Error (DFPE)
[2] Quantum Price Level (QPL)
[3] Mean Recall Precision (MRP)
[4] Mean Success Precision (MSP)
[5] Root Mean Square (RMS)
[6] Mean Absolute Percentage Error (MAPE)
[7] Time Series Prediction (TSP)
[8] Exploratory Projection Pursuit (EPP)
[99] Dynamic Panel Data (DPD)
[10] Latent Dirichlet Allocation (LDA)
[11] ndustrial Production Index (INDPRO)
[12] Consumer Price Index (CPIAUCSL)

TABLE 4. ***(Continued.)*** **Selected articles of market analysis applications category.**

				-CFNAI[1] -NFCI[2] -Accuracy -Performance			
Yang et al. [50]	Mining-based news sentiment analysis framework for business	-Crawler -CNN -Traditional topic extraction tool -Classification -LR[3] -SVM	-Dataset -Simulation (Crawler)	-Performance -F-score	-Improving summary text's readability	-	-
Smith and O'Hare [51]	Correlating changes in stock prices with those of the traditional media and social media	-NLTK[4] -VADER tool[5]	-Dataset -Simulation (Python)	-Correlation	-Feasibility	-Limited period	-Extending time to analyze frequent occurrences -Processing large groups' emotions by ML/DL
Yashina et al. [52]	Financial asset technical analysis in crisis	-NN -Optimization algorithm	-Dataset -Simulation	-CVI[6] -FCDI[7] -SMA[8] -MACD -RSI	-Dynamicity -Applicability -Correctness	-Limited technical indicators	-Expanding anti-crisis indicators toolkit
Shahzad et al. [53]	Linking the oil and gas supply chain using AI	-QVAR[9]	-Implementation -Dataset	-GFEVD[10] -TCI[11]	-Considering green manufacturing	-Limited indicators	-Promoting solutions for companies based on AI
Wang and Zhao [54]	Big data and AI combination for the economy prediction model	-DL -ANN -LSTM -Graph NN	-Dataset -Simulation	-R -RMSE -Accuracy	-Multi-objective	-Basic model	-Developing a real platform -Improving accuracy
Xiangyan [55]	Digital economy prediction using big data and ML	-Time series model	-Dataset -Simulation	-Performance -MSE -Accuracy	-High performance	-Theoretical	-Improving the macroeconomic forecast accuracy

[1] Chicago Fed National Activity Index (CFNAI)
[2] National Financial Conditions Index (NFCI)
[3] Logistic Regression (LR)
[4] Natural Language Tool Kit (NLTK)
[5] Valence Aware Dictionary and sEntiment Reasoner (VADER)
[6] Crisis Volatility Indicator (CVI)
[7] Financial Crisis Depth Indicator (FCDI)
[8] Simple Moving Average (SMA)
[9] Quantile Vector Autoregression (QVAR)
[10] Generalised Forecast Error Variance Decomposition (GFEVD)
[11] Total Connectedness Index (TCI)

years (2011–2017). Using data visualizations of the interconnected relationships between road transportation patterns and macroeconomic indicators, the results clarify the data's fascinating underlying structure. The results of the clustering approaches similarly showed the same data structure. Several accurate predictions were generated by analyzing the road traffic data as a time series and forecasting the future values of the primary series. These findings supported the predicted connection between data on road transportation and macroeconomic indices.

Coulter [46] deployed Natural Language Process to analyze the incidents of international news and Bitcoin price. This research shows a relationship between the news and the price of Bitcoin. Based on the news content, it has been distributed into 18 categories, including crime content related to cryptocurrencies, the economy, and the market. The analyzed result shows some specific terms or words that will cause the price movement of the market, mostly the Bitcoin market. Moreover, the effect mostly happened within 24 hours after the news had been released.

Koch et al. [47] analyzed 34,209 news articles to inspect the connection between stock market fluctuation and news sentiment. This study categorizes news sentiment into three groups: positive, negative, and neutral. Given the analyzed

TABLE 5. The evaluation factors for market analysis applications category.

Research	Accuracy	Performance	Error-related metric	Sentiment-related metric	Completeness	Volatility	Other
Lee [42]	✓		✓				
Khashman and Carstea [43]	✓						
Al-Fattah [44]	✓				✓		
Vekaria et al. [8]	✓		✓				
Alonso de Armiño et al. [45]	✓		✓				
Coulter [46]	✓	✓					
Koch et al. [47]				✓			
Caporale et al. [48]	✓						
Barbaglia et al. [49]	✓	✓		✓			
Yang et al. [50]		✓					
Smith and O'Hare [51]							✓
Yashina et al. [52]		✓				✓	
Shahzad et al. [53]	✓						
Wang and Zhao [54]	✓		✓				
Xiangyan [55]	✓		✓				✓
Total	11	4	5	2	1	1	2

result, when the whole economy is not in a stable scenario, the spillover effect of the news sentiment may assist the investors from the institution in making decisions. Besides, the result also shows that although the directional spillover has a strong effect on the development of BREXIT, not in every scenario. In the end, the impact of the news sentiment does not have a strong connection to the outcome of BREXIT.

Caporale et al. [48] investigated the connections between press indexes and portfolio flows. Meanwhile, this research sorts out a comprehensive factor based on all positive and negative news titles. The period is from 2007 to 2017. As a result, news indexes are the crucial factor influencing cross-border portfolio flows.

Barbaglia et al. [49] produced a method of extracting emotional information from the news based on the current economic scenario. This method can analyze the emotion from two aspects: the meaning of the word or based on the score corresponding with the specific terms. For the experiment, they collected news data from six publishers in the US and a total of 6.6 million articles and 4.2 billion words. As the results show, multiple economy emotion indexes are highly related to the fluctuation of the business cycle. In addition, they also found that including the economic factors and emotional reasons simultaneously can increase the accuracy of the prediction significantly.

Yang et al. [50] built an undirected weight for news topics. The reason is that they found out that sentiment analysis for business has some unsolved issues. Such as, the DL system cannot identify jokes, stories, or words with two meanings. To address this issue, they normalized the sentences in the paper as nodes. As a result, when the system identifies the articles, it will not be limited by a single word. Furthermore, to increase the accuracy of emotion analysis, they mentioned a sentiment analysis named BuSeD. The finding indicated that the sentiment analysis tool has great economic importance.

Smith and O'Hare [51] investigated the link between news sentiment and tweet affection. Some of the CEOs will post a tweet on social media. This research proved it does not have high relation to the stock price of its companies. However, news unrelated to the finical will not affect the stock price. In contrast, the news sentiment of business is associated with stock movements. Nonetheless, the strength of the association suggests that price movement drives sentiment, apart from the tumultuous economic times caused by the SARS-COV-2 pandemic in 2020.

Yashina et al. [52] developed a finical asset analysis tool. The point of this tool is to decrease and improve investment strategies when crises come. Based on the mathematical statistics method, the system can boost investment strategies by indexing fluctuation and economic crises. This system has been evaluated by the dataset of the financial crises of Russia in 2008-2009, 2014-2015, and 2019-2020. With the algorithm of this system, you will be able to monitor the finical market situation in real-time.

Shahzad et al. [53] investigated the relationship between AI enterprises and basic materials/oil & gas companies in Islamic markets. They discovered that AI was a net recipient of shocks and that oil and gas-related companies were the cause-in-quantiles. The authors proposed that COVID-19 provided an opportunity to strengthen the involvement of AI innovations with basic materials and oil and gas companies. The findings have significance for AI application developers, resource policymakers and managers, and investors interested in advanced technologies. AI may be regarded as a crucial link in the supply chain of basic materials and oil and gas businesses.

Wang and Zhao [54] proposed a prediction model based on AI and combining big data analytics. They believe that, due to the limitations of human comprehension, the conventional economic model is less accurate than the modern one. Now, the digital economy accomplishes the goal of economic connectivity and meticulous data sharing so that the statistics of the economy and mathematical analytics will be more accurate. Besides, with the help of AI, it can analyze it more objectively and comprehensively. In their model, they integrate a variety of variables, including potential political issues, human activity elements, and social environment factors. The outcome shows that their developed model can be the basic economic statistics, analysis, and decision-making model.

Xiangyan [55] examined how big data and AI technology have affected economic forecasting and analysis. According to the typical point data paradigm, this study proposes a macroeconomic interval forecasting approach based on the stock market, fund market, and futures market data. After hands-on results demonstrate that the macroeconomic interval prediction model can be reasonably fitted to the Shanghai fund index, futures market transaction amount, Shenzhen component index, and narrow money supply in the interval financial data. The findings of the experimental investigation demonstrate that the suggested model performs well in predicting patterns of economic growth and that it may be applied to projecting upcoming economic development projections.

This paper presents a comparison table summarizing the main features of research conducted in this area, including the main context, applied techniques, evaluation methods, evaluation metrics, benefits, limitations, and future work. We aim to reach valuable results for future studies using the technical and statistical interpretations resulting from comparing these factors.

A summary of the most significant features covered in the analyzed papers in this category is presented in Table 4. Furthermore, Table 5 shows the evaluation factors for this category.

The following results are based on the interpretation from comparing the analyzed papers in this section.

Overarching themes

- AI in economic predictions:

Predicting economic trends and market movements using AI techniques like NNs, clustering, and big data analysis.

- Sentiment Analysis:

Using sentiment analysis in social media and events to assess the impact of the news on the market and make informed investment decisions.

- AI Algorithm Integration:

Enhancing the accuracy of market analysis by combining different AI algorithms.

Emerging trends

- COVID-19 impact analysis:

Using AI to analyze the effects of COVID-19 on various sectors of the economy.

- Linking traditional and social media:

The correlation between traditional media, social media, and stock price.

In the market analysis applications papers, several gaps are identified, which are proposed in the following:

Critical gaps

- Industry-specific applications:

Although many general market analysis papers are available, there is a lack of research on AI applications in specific industries, such as healthcare, energy, or transportation.

- Real-time market monitoring:

Further investigation is required in developing real-time market analysis systems capable of adapting to dynamic market conditions and providing timely insights.

Most applications of AI in market analysis are related to forecasting market trends and prices based on sentiments and other factors. Therefore, accuracy is the most significant metric for evaluating these models' efficiency. The frequency of utilized evaluation metrics supports this conclusion.

C. RISK MANAGEMENT APPLICATIONS

El Qadi et al. [56] focused on credit assessments and executed benchmarks based on different ML models. The objective of this model is to predict whether the company will have a financial problem during the given time horizon. This model will help credit insurance companies decrease risks when providing company loans. The model can evaluate the possibility that the company will break the contract. They give an expert-aligned feature relevance score that identifies the disparity between a credit risk expert and a model feature attribution explanation to quantify the convergence more effectively toward enhanced human-aligned decision-making.

Koo and Kim [57] found that hybrid models integrating ANNs and GARCH-type models have been developed. Still, the fluctuating time series distribution is mainly concentrated at zero. The above reasons make the predictive performance of the overall probability density function domain low because the weights in the network are only trained to the high-frequency region. To address this issue, they suggested a novel hybrid model based on a nonlinear filtering method and a GARCH-type model to lower the volatility concentration feature. They applied a root-type function for the filtering, and according to the study, the suggested hybrid model (VU-GARCH-LSTM) obtained an efficiency gain of 21.03% in RMSE after comparing the data with the average efficiency of the current hybrid model combining LSTM and GARCH-type models. In addition, the model enhances the forecast performance in areas where the label density is likely correct by predicting the distribution to be comparable to the label distribution.

Gonzales and Hargreaves [58] aimed to address the challenge of decision-making in the stock market. They created three distinct approaches to developing a stock recommender system that focuses on the needs and interests of the investors. They used hierarchical clustering to understand groups of traders with similar preferences, which improved computational efficiency. The K-Nearest Neighbor (kNN), Singular Value Decomposition (SVD), and Association Rule

TABLE 6. Selected articles of risk management applications category.

Research	Main context	Applied technique	Evaluation method	Evaluation metric	Benefit	Limitation	Future work
El Qadi et al. [56]	Credit scoring of companies using AI and ML models	-ML -Gradient boosting -eXplainable -RF	- Dataset - Simulation (Python)	-Credit scoring	-High Consistency -High credit score -High Accuracy		-Improving trust in the proposed model
Koo and Kim [57]	Stock market volatility hybrid forecast model	-ANN -LSTM	-Simulation (Adam optimizer) -Dataset	-RMSE -CC[1] -AUC[2] -Extreme	-High probability density -High performance	-	-Modifying the concave function to improve prediction performance
Gonzales and Hargreaves [58]	Stock recommender system to invest' risk management	-Clustering -Collaborative filtering -ARM[3] -SVD[4] -kNN[5]	-Dataset	-VaR[6] -MAE[7] -RMSE -AP@K -RoR[8]	-Computational efficiency -	-Outdated dataset	-Incorporating stock price forecasting -Incorporating more users in the construction -Incorporating other trading platforms
Fafaliou et al. [59]	Market longevity and ESG reputational risk	-KZI[9]	-Dataset - Implementation	-SAI[10] -Tobin's Q	-Sustainability	-	Integrating ESG reputational risk considerations.
Gangwar et al. [60]	Plants' production scheduling optimization by scenario and risk analysis using AI	-MCSG[11] -Time series (ARIMA) -MILP[12] -Monte-Carlo	-Dataset -Simulation (MATLAB)	- Performance - -Time -Accuracy -RiskΩ -VaR -CVaR[13]	-Reliability -Using the real dataset -Minimizing risk -Preventing economic penalties	-Lack of parallel computation	-Applying the proposed method to other energy-intensive industries -Utilizing spot electricity market predictions to optimize contracted power -Reducing power contract breach losses
Ahmed et al. [61]	Banking risk assessment system using ML and	-DT[14] -SVM -GA -ANN	-Dataset -Simulation (MATLAB)	-Accuracy - Performance -RRI[15]	- Comprehensively risk assessment in banking	-Not considering performance	-Investigating risk and banking performance -Risk analysis of local banking regulations

[1] Correlation Coefficient (CC)
[2] Area Under Curve (AUC)
[3] Association Rule Mining (ARM)
[4] Singular Value Decomposition (SVD)
[5] K-Nearest Neighbor (kNN)
[6] Value at Risk (VaR)
[7] Mean Absolute Error (MAE)
[8] Rate of Return (RoR)
[9] Kolmogorov-Zurbenko Index (KZI)
[10] System Adequacy Index (SAI)
[11] Monte-Carlo scenario generator (MCSG)
[12] Mixed Integer Linear Programming (MILP)
[13] Conditional Value at Risk (CVaR)
[14] Decision Tree (DT)
[15] Risk Ranking Indicator (RRI)

Mining (ARM) algorithms were investigated and tested. The expected returns and value-at-risks were assessed to ensure profitability and support risk-informed decisions. The average rate of return for the short-term, medium-term, and long-term portfolios was 4.15 %, 10.24 %, and 23.17 %, respectively.

Fafaliou et al. [59] investigated the impact of Environmental, Social, and Governance (ESG) reputational risk on the market durability of a sample of US-traded corporations from 2007 to 2019. They used dynamic empirical analysis to evaluate the correlation between firms' ESG reputational risk and market durability. They discovered that ESG reputational risk negatively impacted company growth opportunities, limiting market durability. The authors confirmed their empirical findings through several robustness checks, providing useful insights for stakeholders and market participants.

Gangwar et al. [60] developed a hybrid simulation-optimization approach that combines scenario and risk analysis to optimize production plant scheduling under volatile energy conditions. Despite traditional methods' mathematical complexity, the authors attempted to overcome their slowness and inapplicability. This approach was

TABLE 6. *(Continued.)* **Selected articles of risk management applications category.**

Rodríguez-Espíndola et al. [62]	optimization techniques Using AI in digital manufacturing risk management	-Optimization techniques -EFA[2] -SEM	-Simulation -Dataset	-SR -NIMR[1] -RMSEA[3] -KMO[4] -GFI[5] -TLI[6] -CFI[7] -Normed X^2	-Improving operational productivity	-Small sample -Not considering case study	-Investigating the effect of each technology in specific scope of risk management

[1] Net Interest Margin Ratio (NIMR)
[2] Exploratory Factor Analysis (EFA)
[3] Root Mean Square Error of Approximation (RMSEA)
[4] Kaiser-Meyer-Olkin (KMO)
[5] Goodness-of-Fit Index (GFI)
[6] Tucker-Lewis Index (TLI)
[7] Comparative Fit Index (CFI)

used to optimize the operation of a cryogenic air separation plant under the uncertainty of electricity prices for short-term scheduling. Based on MATLAB and a dataset collected from a cryogenic air separation plant in Tarragona, Spain, they evaluated their model. This approach can be easily adapted to scheduling facilities in several energy-intensive industries, such as metallurgy, cement, or pulp and paper manufacturing.

Ahmed et al. [61] measured bank risk using the Mahalanobis Distance (MD) and an Adaptive Neuro-Fuzzy Inference System within five categories: Capital Adequacy, Credit, Liquidity, Earnings Quality, and Operational Risk. Based on datasets and simulations with MATLAB, they examined different risk indexes and the functional model's sensitivity. As a result, the Net Interest Margin Ratio (NIMR) and the Credit Adequacy Ratio (CAR) are the most significant factors in determining bank risk. In contrast, the Provisional Loan Ratio (PLR) is disappointing. Using ANNs and optimization techniques is also beneficial in evaluating credit risk.

Rodríguez-Espíndola et al. [62] developed a risk management behavioral model combining AI, big data, cloud computing, and blockchain technologies with institutional theory.

Table 6 shows a summary analysis of selected articles in this category. Furthermore, Table 7 shows the evaluation factors for this category.

This paper presents a comparison table summarizing the main features of research conducted in this area, including the main context, applied techniques, evaluation methods, evaluation metrics, benefits, limitations, and future work. We aim to reach valuable results for future studies using the technical and statistical interpretations resulting from comparing these factors.

The following results are based on the interpretation from comparing the analyzed papers in this section.

Overarching themes

- Credit risk assessment:

Companies' credit risk analysis and banking risk management optimization using AI and ML.

- Forecasting Market Volatility: Utilizing AI-based volatility forecasting models for risk assessment and portfolio management.
- Integration of AI in Manufacturing and Supply Chain: AI in risk management beyond the financial sector to the manufacturing industries.

Emerging trends

- ESG reputational risk:

Using AI to assess and manage reputational risk related to ESG factors.

- Digital Manufacturing risk analysis:

Digital manufacturing processes risk analysis using integrated AI, including supply chain management and optimization.

Critical gaps

- Explainability and transparency:

A transparent and explainable risk management system is needed for gaining trust and mitigating risks.

- Real-time risk assessment:
  There is a need to develop real-time risk assessment systems that can adapt to provide timely risk alerts

We present a grouping of metrics that measure similar factors based on evaluation metrics used in AI-based risk management applications. The relevance and importance of these metrics will vary depending on the specific context and objectives of the AI-based risk management application.

- Accuracy: It generally refers to the correctness or precision of predictions made by an AI-based risk management model.
- Performance: Metrics like RoR, Tobin's Q, and performance are associated with evaluating a risk management strategy's financial performance or profitability.
- Risk assessment: Metrics such as VaR, CVaR, Extreme (extreme value analysis), RiskΩ, RRI, SR, NIMR,

TABLE 7. The evaluation factors for the risk management applications category.

Research	Accuracy	Performance	Risk assessment metric	Model evaluation metric	Data Analysis and ML	Profitability
El Qadi et al. [56]	✓		✓			
Koo and Kim [57]	✓	✓	✓			
Gonzales and Hargreaves [58]	✓	✓	✓	✓	✓	✓
Fafaliou et al. [59]		✓	✓			
Gangwar et al. [60]	✓	✓	✓			
Ahmed et al. [61]	✓		✓			
Rodríguez-Espíndola et al. [62]					✓	
Total	5	4	6	1	2	1

and Kaiser-Meyer-Olkin (KMO) are indicators of risk assessment and the ability of a risk management model to measure and quantify potential risks.

- Model evaluation metrics: Metrics such as RMSE, MAE, AP@k (Average Precision at k), RMSEA, Goodness of Fit Index (GFI), Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), and Normed X2 are used to assess the performance and accuracy of the risk management model itself.
- Data analysis and ML metrics: Metrics like Correlation Coefficient (CC), Area Under the Curve (AUC), kNN, SVD, ARM, Kolmogorov-Zurbenko Index (KZI), and Worst-Case Weighted Importance (WWI) are associated with data analysis techniques, ML algorithms, or feature importance.

Based on repeated assessment criteria, accuracy is the most significant criterion in this category. In addition, as the name of this category indicates, the criteria related to risk measurement are more critical.

IV. DISCUSSION

The previous section reviewed the AI applications in three categories of the economy, including stock trading, market analysis, and risk management. In this section, we answer the predefined RQs based on technical and statistical analysis and visually report the results.

- RQ1: Which branches of AI are applied in economics?

According to the techniques that are involved in the analyzed research papers, the AI branches applied in the economy can be summarized as follows:

Notably, time series analysis is frequently used in the economy, not considered a subfield of AI, but a statistical analysis technique used to analyze and model time-dependent data. Furthermore, ARIMA and SARIMAX can be applied to AI applications, are not associated with a specific branch of AI, and are widely used in statistical analysis and forecasting.

Figure 4 shows the applied AI branches in the economy.

- RQ2: What are the challenges associated with AI applications in the economy?

AI is becoming more and more important to the economy. This is because AI technologies make businesses more efficient and productive. While AI offers immense potential for economic forecasting, it also presents several challenges. Some challenges are:

A. ACCURACY

AI models are often used to predict economic trends and make financial decisions. However, due to the complexity of the global economy, these models can be prone to errors and inaccuracies. AI models are based on algorithms and often rely on incomplete or outdated data, which can lead to inaccurate predictions. Additionally, AI models are often unable to learn and adapt to changes in the economy as quickly as needed, meaning they may not accurately predict future outcomes. Also, the accuracy of AI-based economic predictions depends on the data quality used to train the AI system. For the training data to be reliable, it needs to be up-to-date and reflect the current state of the economy. The AI system will produce inaccurate results if the data is outdated or incomplete [8].

B. EXTERNAL IMPACTS

To make a prediction model in an AI application, we usually need historical data to train and test the model. We can also modify or combine different algorithms to improve the accuracy of the prediction. Still, external factors, such as financial storms, corporate reform, negative news, and major disasters, will affect the stock price. Therefore, we hope to discover the cycles or patterns of these external factors that will affect stock prices [35].

C. BIAS

Another challenge of AI in the economy's prediction is bias. AI models often rely on historical data to make predictions, which can be biased. If a dataset contains a certain bias, this can be reflected in the AI model's predictions and lead to inaccurate or unfair results. Additionally, AI models can be vulnerable to malicious actors who may manipulate the data to manipulate the results [63].

D. COMPLEXITY

AI models often require a large amount of data to make accurate predictions. This data often needs to be collected from multiple sources, which can be difficult and time-consuming. Additionally, the AI models themselves can be complex and

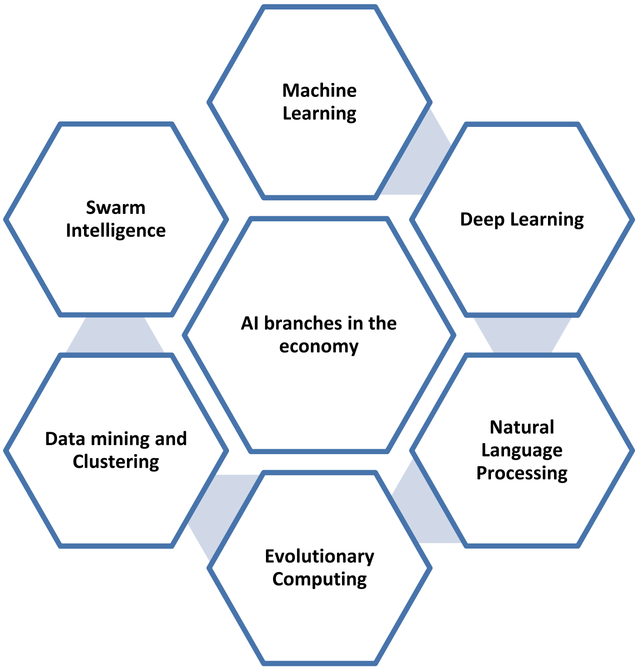

FIGURE 4. Applied AI branches in the economy.

require a lot of computing power, which can be expensive and difficult to obtain [10].

Human Interaction: Another challenge of AI in the economy's prediction is that AI models cannot accurately predict human behavior. AI models often cannot accurately predict how people will respond to certain events or react to certain economic conditions. This means that AI models may not accurately predict the effects of certain events on the economy [64].

E. REAL-TIME TRADING STRATEGIES

Development of strategies that can quickly adjust to market changes.

F. GENERALIZATION OF MODELS

The development of AI models can work across various financial markets.

G. MODEL EVALUATION AND ROBUSTNESS

Assuring that AI-based trading models are reliable and resilient to various scenarios.

H. INDUSTRY-SPECIFIC APPLICATIONS

Expanding research on AI applications in specific industries like healthcare, energy, or transportation.

I. REAL-TIME MARKET MONITORING

Enhancing real-time market analysis systems and providing timely market insights.

J. EXPLAINABILITY AND TRANSPARENCY

Development of transparent risk management systems to build trust and enable AI-driven decision-making to be understood.

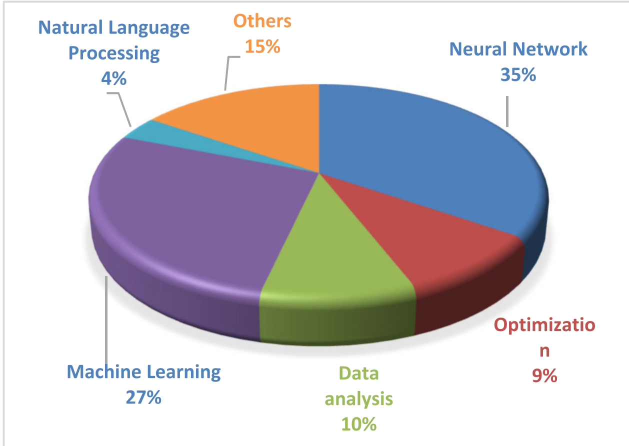

FIGURE 5. The AI techniques applied in the economy.

K. REAL-TIME RISK ASSESSMENT

Establishing systems for assessing risks continuously in real-time and providing timely alerts.

It is essential to adjust to market changes, create effective models across multiple markets, evaluate the performance and reliability of these models, explore AI applications within specific industries, monitor markets in real-time, ensure transparency in decision-making, and assess risks accordingly.

- RQ3: Which techniques are most commonly used in AI applications in the economy?

We integrated AI techniques belonging to the same AI subfields to estimate the percentage of applications of each AI branch in the economy. Figure 5 illustrates the portion of applications in each category:

The graph shows that NNs, with 35%, are the most commonly used AI techniques in the economy, followed by ML techniques, with 27%.

- RQ4: What are the most significant evaluation metrics for AI applications in the economy?

After investigating and analyzing selected papers, we found the objectives that all articles focus on, among which accuracy and correct prediction rate are the most concerned. The results are shown in Figure 6.

RQ5: What are the current open issues and future directions of AI in the economy?

The most important open issues of AI for the economy can be:

1. Increasing automation and job losses: AI is rapidly becoming more common in the economy, leading to increased automation and job losses. AI technology is being used to replace human labor in many industries, from manufacturing to financial services. As AI technology continues to improve and become more widespread, more and more jobs will likely be replaced by machines and robots. This will lead to increased inequality, as those with the skills to work with AI technology will reap the benefits, while those without those

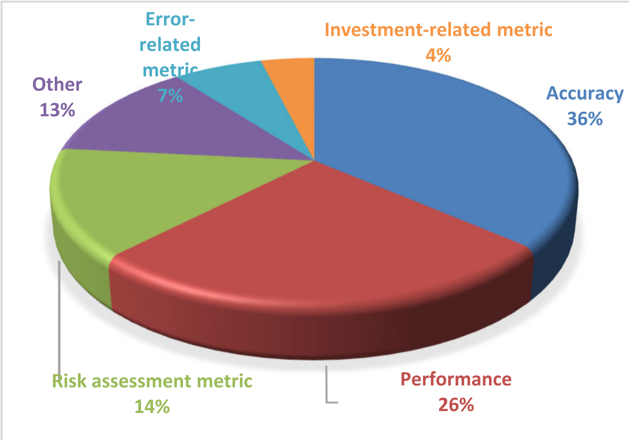

FIGURE 6. The evaluation metrics applied AI in the economy.

skills may struggle to find work. Additionally, using AI can decrease wages for those employed, as machines can work for less than humans and do not require the same benefits. This can decrease overall wages for those employed in the economy, decreasing consumer purchasing power [52].

2. Data privacy and security: AI has recently been increasingly implemented into the economy, and its potential for revolutionizing our business is immense. However, as with any rapidly evolving technology, certain risks are associated with using AI. One of the most pressing concerns is data privacy and security. AI relies on large data sets to make decisions, meaning that any data collected by companies using AI must be carefully safeguarded from potentially malicious actors. Companies need robust data security processes to ensure that any collected data is not exposed to outside parties while allowing AI to function properly. Furthermore, companies should also consider how they will protect their customers' data and how they could be held accountable for any potential misuse of this data. By addressing these issues, companies can ensure that their use of AI is as secure and ethical as possible, allowing them to benefit from this technology without compromising their customers' privacy [53].

3. Regulatory challenges: Regulatory challenges, in particular, are a major obstacle to the growth of AI in the economy. AI-based systems are complex and highly dynamic, making it difficult to create effective laws that govern their use. Furthermore, due to the global nature of AI, it is not easy to create laws that are both effective and applicable across multiple jurisdictions. Privacy and data security are also major concerns when using AI, as the large amounts of data collected can be used to identify individuals, track their movements, and influence their behavior. Finally, the potential for AI to create or displace jobs is a key area of concern, as introducing AI technologies could drastically reduce the number of jobs available in certain fields. Governments must create regulations that protect workers from displacement and ensure that the benefits of AI are distributed fairly [54].

4. Ethical implications: AI can potentially revolutionize the economy but also presents important ethical issues. A major concern is the impact on employment. Automation could create economic displacement as machines increasingly replace human labor, especially in the service sector. This could lead to a significant rise in unemployment and could exacerbate existing income inequality. Another ethical issue is privacy. AI systems are increasingly used to collect and analyze data, making it important to consider the implications of this data collection and what rights citizens have to their data. Additionally, there is a need to ensure equitable access to AI to share its benefits widely and not concentrated in certain areas or groups. These ethical considerations must be addressed to ensure that AI is used responsibly and for the benefit of all [55].

5. Economic impact: AI has become a transformational economic force. AI has had a major impact on the healthcare, finance, logistics, manufacturing, and retail industries. AI automates mundane tasks, optimizes processes, and predicts customer behavior. AI is also helping to improve customer service, increase efficiency, and reduce costs. AI is also helping to increase the accuracy of data analysis, which can provide valuable insights that can lead to better decision-making. In addition, AI is being used to drive innovation and create new products and services. AI is changing the way businesses operate, leading to increased customer satisfaction and improved customer loyalty. AI also drives increased productivity and efficiency, helping businesses remain competitive globally. AI is also helping to create new job opportunities, as it opens up new fields and roles for human workers. The overall impact of AI on the economy is profound, and its potential is yet to be fully realized [56].

The following are some possible future directions for AI in the economy:

1. Cryptocurrency: The increasing popularity of cryptocurrencies allows researchers to study AI's impact on digital currencies and the global economy. AI plays an important role in predicting cryptocurrency prices through data analysis, pattern recognition, and ML [65]. It identifies cryptocurrency trading trends, predicts future prices, and detects fraud and money laundering. Here is an overview of how AI is applied to cryptocurrency price predictions:

- Data analysis: AI algorithms, including price movements, trading volumes, market sentiment, and other factors, can analyze a wide range of historical cryptocurrency data. AI models can identify patterns, correlations, and anomalies in cryptocurrency prices.
- Pattern Recognition: Identifying patterns in complex data sets is one of the most valuable abilities of AI. Several AI algorithms can identify patterns in historical price charts, such as support and resistance levels, chart patterns, and other technical indicators. These patterns can provide insights into future price movements.
- ML: Predictive models can be developed using AI models that learn from historical cryptocurrency data. It is possible to establish relationships between various

factors and the movement of cryptocurrency prices through training ML algorithms on vast datasets. These models can predict based on new data inputs and changing market conditions [66].
- Sentiment analysis: AI-powered sentiment analysis techniques analyze social media posts, news articles, and online cryptocurrency discussions. AI models can identify potential price influences by gauging the sentiment of market participants. As a result of this analysis, short-term market sentiment can be predicted, and its potential impact on price trends can be evaluated.
- Hybrid approaches: Many cryptocurrency price prediction models combine multiple AI techniques. In some models, data is incorporated from various sources, including market data, news sentiment, social media sentiment, and macroeconomic indicators. Combining multiple AI approaches, these hybrid models are intended to provide more accurate and robust predictions.

2. Exchange rate fluctuations: AI plays a significant role in analyzing and predicting exchange rate fluctuations. The proposed taxonomy shows that AI can predict exchange rate fluctuations through data analysis, predictive modeling, sentiment analysis, news and event impact analysis, and algorithmic trading. It is important to note that various complex factors affect exchange rate fluctuations, including economic indicators, political events, market sentiment, and global economic trends. Exchange rates remain subject to many unpredictable factors, despite AI's ability to provide valuable insights. Therefore, AI supports decision-making and improves forecasting accuracy but does not guarantee exact predictions of exchange rate movements. This challenge is a potential direction for in-depth research.

3. Accounting fraud detection: AI can detect accounting fraud using advanced algorithms and data analysis techniques. The following are some ways in which AI can detect accounting fraud:

- Anomaly Detection
- Pattern Recognition
- NLP
- Data Integration and Analysis
- Predictive Analytics
- Network Analysis
- Continuous Monitoring

These AI-driven techniques can be combined with human expertise in forensic accounting and fraud investigation to enhance the ability to detect accounting fraud, mitigate risks, and protect financial integrity. Accounting fraud detection and prevention efforts are significantly strengthened by AI's ability to process vast amounts of data, detect subtle patterns, and provide timely alerts.

4. NLP: With NLP, AI can analyze news articles, financial reports, and other documents related to the economy. This can help researchers identify emerging trends and make informed decisions about investment opportunities [67].

5. ML algorithms for trading: ML algorithms can be used to develop trading strategies that automatically adjust to changing market conditions. This can potentially increase profits and reduce risk [68].

6. Risk management: AI can be used to analyze data related to financial risks, such as credit risk, market risk, and operational risk. This can help financial institutions manage risk more effectively and make better decisions about lending and investing [69].

V. REAL CASES

Here, we provide several real cases to support the AI application scenarios discussed in this paper:

- Renaissance Technologies,[1] or RenTech, is an American hedge fund and investment management firm based in East Setauket, New York, specializing in systematic trading using quantitative models derived from mathematical and statistical analysis in the design and execution of its investment programs.
- Virtu Financial,[2] a leading high-frequency trading firm, is a notable case study in high-frequency trading which is an American company that provides financial services, trading products, and market-making services. Virtu employs sophisticated AI algorithms to analyze vast market data and execute trades within milliseconds.
- Trade Ideas[3] uses AI-based pattern recognition algorithms to identify trading opportunities. As a result of their algorithms, users receive real-time trading alerts based on technical patterns, such as moving averages, support and resistance levels, and chart patterns.
- Wealthfront[4] is a robo-advisor platform that utilizes AI algorithms to optimize portfolio composition and suggest optimal asset allocations and rebalancing strategies to help clients reach their financial objectives. It considers risk tolerance, investment goals, and historical performance.
- AlphaSense[5] provides financial forecasting and predictive analytics using AI. Using a wide range of data, including financial statements, news articles, and industry reports, AlphaSense assists users in making accurate predictions about the earnings of companies, the movement of stock prices, and the direction of the market.
- MarketPsych[6] specializes in market sentiment analysis. They use AI algorithms to process vast amounts of news articles, social media posts, and other textual data to gauge market sentiment. Their sentiment indicators give traders and investors insights into the market's mood.
- MSCI Barra[7] is a prominent provider of market segmentation solutions that uses AI techniques to classify stocks

[1]https://www.rentec.com/Home.action?index=true
[2]://www.virtu.com/
[3]https://www.trade-ideas.com/
[4]https://www.wealthfront.com/
[5]https://www.alpha-sense.com/
[6]https://www.marketpsych.com/home
[7]https://www.msci.com/

and assets into various indices and segments based on factors such as industry classifications, geographical regions, and market capitalizations. By using these segmented indices, investors can monitor the performance of specific market segments.

- PayPal,[8] an online payment platform, utilizes AI algorithms for fraud detection. These algorithms analyze transaction data, user behavior patterns, and other factors to identify and prevent fraud, ensuring financial transaction security.
- LendingClub,[9] a peer-to-peer lending platform, uses AI algorithms to assess loan applicants' creditworthiness. Using AI to analyze credit histories, income data, and other factors, LendingClub's system determines the risk associated with each loan request, allowing them to make informed lending decisions.
- BlackRock[10] is a leading investment management firm that uses AI-based risk management tools to assess market risks. Their system analyzes market indicators, economic data, and portfolio positions to identify potential risks. It also conducts stress tests on investment portfolios, enabling proactive risk management.

VI. CONCLUSION

In conclusion, AI has the potential to transform the economy by increasing efficiency, reducing costs, and generating new sources of value. It has the potential to create new opportunities for those who are willing to embrace it and have a significant impact on the way businesses operate. As AI technology continues to evolve and become more accessible, it is essential to recognize the potential consequences of its widespread adoption. Governments and businesses must consider optimal ways to manage and regulate AI to ensure it is utilized responsibly and ethically. At the same time, it is essential to recognize the potential for AI to create new economic opportunities and open up new collaboration and innovation avenues. By understanding the implications of AI and developing the necessary policies and regulations, the economy can reap the benefits of AI without sacrificing human dignity and social justice. This paper examines several application scenarios, such as stock market predictions, oil price analysis and forecasting, and research on how AI may impact the global economy. Using DL, numerous research articles predict the direction of the economy. High accuracy rates are achieved in all employed models; some are even efficient or offer other benefits. Furthermore, the article demonstrates that numerous techniques are applied to the data, with DL carrying the most weight. Finally, we hope to be focused on applications of cryptocurrency price predictions, exchange rate fluctuations in macro and microeconomics, and detecting accounting fraud illegally performed by companies in the future.

[8]https://www.paypal.com/
[9]https://www.lendingclub.com/
[10]https://www.blackrock.com/ca

REFERENCES

[1] T. Cui, S. Ding, H. Jin, and Y. Zhang, "Portfolio constructions in cryptocurrency market: A CVaR-based deep reinforcement learning approach," *Econ. Model.*, vol. 119, Feb. 2023, Art. no. 106078.
[2] Q. Y. E. Lim, Q. Cao, and C. Quek, "Dynamic portfolio rebalancing through reinforcement learning," *Neural Comput. Appl.*, vol. 34, no. 9, pp. 7125–7139, May 2022.
[3] J. Jang and N. Seong, "Deep reinforcement learning for stock portfolio optimization by connecting with modern portfolio theory," *Expert Syst. Appl.*, vol. 218, May 2023, Art. no. 119556.
[4] S. A. Saeidi, F. Fallah, S. Barmaki, and H. Farbeh, "A novel neuromorphic processors realization of spiking deep reinforcement learning for portfolio management," in *Proc. Design, Autom. Test Eur. Conf. Exhib. (DATE)*, Mar. 2022, pp. 68–71.
[5] V. M. Ngo, H. H. Nguyen, and P. Van Nguyen, "Does reinforcement learning outperform deep learning and traditional portfolio optimization models in frontier and developed financial markets?" *Res. Int. Bus. Finance*, vol. 65, Apr. 2023, Art. no. 101936.
[6] H. Li, "Application of artificial intelligence control system in economic management," in *Proc. Int. Conf. Comput. Technol., Electron. Commun. (ICCTEC)*, Dec. 2017, pp. 933–938.
[7] Y. Chen, "Based on neural network prediction and decision-making methods in environmental economy application research in the system," in *Proc. IEEE Int. Conf. Artif. Intell. Ind. Design (AIID)*, May 2021, pp. 100–103.
[8] D. Vekaria, A. Kumari, S. Tanwar, and N. Kumar, "ξ*boost*: An AI-based data analytics scheme for COVID-19 prediction and economy boosting," *IEEE Internet Things J.*, vol. 8, no. 21, pp. 15977–15989, Nov. 2021.
[9] M. Zhang, "Artificial intelligence and application in finance," in *Proc. 11th Int. Conf. E-Educ., E-Bus., E-Manag., E-Learn.*, 2020, pp. 317–322.
[10] L. Cao, Q. Yang, and P. S. Yu, "Data science and AI in FinTech: An overview," *Int. J. Data Sci. Anal.*, vol. 12, no. 2, pp. 81–99, Aug. 2021.
[11] J. Shah, D. Vaidya, and M. Shah, "A comprehensive review on multiple hybrid deep learning approaches for stock prediction," *Intell. Syst. Appl.*, vol. 16, Nov. 2022, Art. no. 200111.
[12] L. N. Mintarya, J. N. M. Halim, C. Angie, S. Achmad, and A. Kurniawan, "Machine learning approaches in stock market prediction: A systematic literature review," *Proc. Comput. Sci.*, vol. 216, pp. 96–102, Jan. 2023.
[13] D. Sheth and M. Shah, "Predicting stock market using machine learning: Best and accurate way to know future stock prices," *Int. J. Syst. Assurance Eng. Manage.*, vol. 14, no. 1, pp. 1–18, Feb. 2023.
[14] Y.-T. Chang and N.-H. Fan, "A novel approach to market segmentation selection using artificial intelligence techniques," *J. Supercomput.*, vol. 79, no. 2, pp. 1235–1262, Feb. 2023.
[15] Y. Zhang, S. Ye, J. Liu, and L. Du, "Impact of the development of FinTech by commercial banks on bank credit risk," *Finance Res. Lett.*, vol. 55, Jul. 2023, Art. no. 103857.
[16] H. Pallathadka, E. H. Ramirez-Asis, T. P. Loli-Poma, K. Kaliyaperumal, R. J. M. Ventayen, and M. Naved, "Applications of artificial intelligence in business management, e-commerce and finance," *Mater. Today: Proc.*, vol. 80, pp. 2610–2613, 2023.
[17] B. J. Rothschild, J. S. Ault, and S. G. Smith, "A systems science approach to fisheries stock assessment and management," in *Stock Assessment*. Boca Raton, FL, USA: CRC Press, 2023, pp. 473–492.
[18] D. Liang, Y. Xu, Y. Hu, and Q. Du, "Intraday return forecasts and high-frequency trading of stock index futures: A hybrid wavelet-deep learning approach," *Emerg. Markets Finance Trade*, vol. 59, no. 7, pp. 2118–2128, 2023.
[19] G. Cohen, "Intraday algorithmic trading strategies for cryptocurrencies," *Rev. Quant. Finance Accounting*, vol. 61, pp. 395–409, May 2023.
[20] X. Kan, M. Miao, L. Cao, T. Xu, Y. Li, and J. Jiang, "Stock price prediction based on artificial neural network," in *Proc. 2nd Int. Conf. Mach. Learn., Big Data Bus. Intell. (MLBDBI)*, Oct. 2020, pp. 182–185.
[21] S. S. Kuma, D. Chitradevi, and S. Rajan, "Stock price prediction using deep learning LSTM (long short-term memory)," in *Proc. 2nd Int. Conf. Adv. Comput. Innov. Technol. Eng. (ICACITE)*, Apr. 2022, pp. 1787–1791.
[22] P. Zhao, S. Yin, B. V. D. Kumar, and T. J. Yew, "Improving quantitative stock trading prediction based on MAD using Q-learning technology," in *Proc. Int. Conf. Artif. Intell. Smart Commun. (AISC)*, Jan. 2023, pp. 57–60.
[23] M.-C. Lee, J.-S. Liao, S.-C. Yeh, and J.-W. Chang, "Forecasting the short-term price trend of Taiwan stocks with deep neural network," in *Proc. 11th Int. Conf. E-Educ., E-Bus., E-Manag., E-Learn.*, 2020, pp. 296–299.

[24] P. Kumar, S. Adhikari, P. Agarwal, and A. Sahoo, "Stock prices prediction based on social influence & historic data," in *Proc. 14th Int. Conf. Contemp. Comput.*, Aug. 2022, pp. 276–283.
[25] D. Selvamuthu, V. Kumar, and A. Mishra, "Indian stock market prediction using artificial neural networks on tick data," *Financial Innov.*, vol. 5, no. 1, pp. 1–12, Dec. 2019.
[26] V.-D. Ta, C.-M. Liu, and D. Addis, "Prediction and portfolio optimization in quantitative trading using machine learning techniques," in *Proc. 9th Int. Symp. Inf. Commun. Technol.*, 2018, pp. 98–105.
[27] M. S. Farahani and S. H. R. Hajiagha, "Forecasting stock price using integrated artificial neural network and metaheuristic algorithms compared to time series models," *Soft Comput.*, vol. 25, no. 13, pp. 8483–8513, Jul. 2021.
[28] T. Sanboon, K. Keatruangkamala, and S. Jaiyen, "A deep learning model for predicting buy and sell recommendations in stock exchange of Thailand using long short-term memory," in *Proc. IEEE 4th Int. Conf. Comput. Commun. Syst. (ICCCS)*, Feb. 2019, pp. 757–760.
[29] A. Safari and A. A. Ghavifekr, "International stock index prediction using artificial neural network (ANN) and Python programming," in *Proc. 7th Int. Conf. Control, Instrum. Autom. (ICCIA)*, Feb. 2021, pp. 1–7.
[30] H. D. Chacón, E. Kesici, and P. Najafirad, "Improving financial time series prediction accuracy using ensemble empirical mode decomposition and recurrent neural networks," *IEEE Access*, vol. 8, pp. 117133–117145, 2020.
[31] S. M. Carta, S. Consoli, L. Piras, A. S. Podda, and D. R. Recupero, "Explainable machine learning exploiting news and domain-specific lexicon for stock market forecasting," *IEEE Access*, vol. 9, pp. 30193–30205, 2021.
[32] I. Ghosh, T. D. Chaudhuri, E. Alfaro-Cortés, M. Gámez, and N. García, "A hybrid approach to forecasting futures prices with simultaneous consideration of optimality in ensemble feature selection and advanced artificial intelligence," *Technol. Forecasting Social Change*, vol. 181, Aug. 2022, Art. no. 121757.
[33] H. Liu, T. Zhao, S. Wang, and X. Li, "A stock rank prediction method combining industry attributes and price data of stocks," *Inf. Process. Manage.*, vol. 60, no. 4, Jul. 2023, Art. no. 103358.
[34] M.-C. Lee, J.-W. Chang, J. Hung, and B.-L. Chen, "Exploring the effectiveness of deep neural networks with technical analysis applied to stock market prediction," *Comput. Sci. Inf. Syst.*, vol. 18, no. 2, pp. 401–418, 2021.
[35] X. Peng, S. Mousa, M. Sarfraz, N. Abdelmohsen A, and M. Haffar, "Improving mineral resource management by accurate financial management: Studying through artificial intelligence tools," *Resour. Policy*, vol. 81, Mar. 2023, Art. no. 103323.
[36] T.-H. Tang, C.-C. Chen, H.-H. Huang, and H.-H. Chen, "Retrieving implicit information for stock movement prediction," in *Proc. 44th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2021, pp. 2010–2014.
[37] Ó. F. Vicente, F. F. Rebollo, and F. J. G. Polo, "Deep Q-learning market makers in a multi-agent simulated stock market," in *Proc. 2nd ACM Int. Conf. AI Finance*, Nov. 2021, pp. 1–9.
[38] M.-Y. Day and J.-T. Lin, "Artificial intelligence for ETF market prediction and portfolio optimization," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining (ASONAM)*, Aug. 2019, pp. 1026–1033.
[39] F. Xu and S. Tan, "Dynamic portfolio management based on pair trading and deep reinforcement learning," in *Proc. 3rd Int. Conf. Comput. Intell. Intell. Syst.*, Nov. 2020, pp. 50–55.
[40] P. Chhajer, M. Shah, and A. Kshirsagar, "The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction," *Decis. Anal. J.*, vol. 2, Mar. 2022, Art. no. 100015.
[41] P. K. Illa, B. Parvathala, and A. K. Sharma, "Stock price prediction methodology using random forest algorithm and support vector machine," *Mater. Today, Proc.*, vol. 56, pp. 1776–1782, Jan. 2022.
[42] R. S. T. Lee, "Chaotic type-2 transient-fuzzy deep neuro-oscillatory network (CT2TFDNN) for worldwide financial prediction," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 4, pp. 731–745, Apr. 2020.
[43] A. Khashman and C.-G. Carstea, "Oil price prediction using a supervised neural network," *Int. J. Oil, Gas Coal Technol.*, vol. 20, no. 3, pp. 360–371, 2019.
[44] S. M. Al-Fattah, "Artificial intelligence approach for modeling and forecasting oil-price volatility," *SPE Reservoir Eval. Eng.*, vol. 22, no. 3, pp. 817–826, Aug. 2019.
[45] C. A. D. Armiño, M. Á. Manzanedo, and Á. Herrero, "Analysing the intermeshed patterns of road transportation and macroeconomic indicators through neural and clustering techniques," *Pattern Anal. Appl.*, vol. 23, no. 3, pp. 1059–1070, Aug. 2020.
[46] K. A. Coulter, "The impact of news media on Bitcoin prices: Modelling data driven discourses in the crypto-economy with natural language processing," *Roy. Soc. Open Sci.*, vol. 9, no. 4, Apr. 2022, Art. no. 220276.
[47] A. Koch, T. L. D. Huynh, and M. Wang, "News sentiment and international equity markets during BREXIT period: A textual and connectedness analysis," *Int. J. Finance Econ.*, early access, May 2022.
[48] G. M. Caporale, F. Menla Ali, F. Spagnolo, and N. Spagnolo, "Cross-border portfolio flows and news media coverage," *J. Int. Money Finance*, vol. 126, Sep. 2022, Art. no. 102638.
[49] L. Barbaglia, S. Consoli, and S. Manzan, "Forecasting with economic news," *J. Bus. Econ. Statist.*, vol. 41, no. 3, pp. 708–719, 2022.
[50] M. Yang, B. Jiang, Y. Wang, T. Hao, and Y. Liu, "News text mining-based business sentiment analysis and its significance in economy," *Frontiers Psychol.*, vol. 13, Jul. 2022, Art. no. 918447.
[51] S. Smith and A. O'Hare, "Comparing traditional news and social media with stock price movements; which comes first, the news or the price change?" *J. Big Data*, vol. 9, no. 1, pp. 1–20, Dec. 2022.
[52] N. Yashina, O. Kashina, S. Yashin, N. Pronchatova-Rubtsova, and I. Khorosheva, "Digital methods of technical analysis for diagnosis of crisis phenomena in the financial market," *Int. J. Technol.*, vol. 13, no. 7, pp. 1403–1411, 2022.
[53] U. Shahzad, M. G. Asl, M. Panait, T. Sarker, and S. A. Apostu, "Emerging interaction of artificial intelligence with basic materials and oil & gas companies: A comparative look at the Islamic vs. conventional markets," *Resour. Policy*, vol. 80, Jan. 2023, Art. no. 103197.
[54] L. Wang and L. Zhao, "Digital economy meets artificial intelligence: Forecasting economic conditions based on big data analytics," *Mobile Inf. Syst.*, vol. 2022, Oct. 2022, Art. no. 7014874.
[55] P. Xiangyan, "Prediction algorithm of digital economy development trend based on big data," *Math. Problems Eng.*, vol. 2022, pp. 1–10, Apr. 2022.
[56] A. E. Qadi, M. Trocan, N. Díaz-Rodríguez, and T. Frossard, "Feature contribution alignment with expert knowledge for artificial intelligence credit scoring," *Signal, Image Video Process.*, vol. 17, no. 2, pp. 427–434, Mar. 2023.
[57] E. Koo and G. Kim, "A hybrid prediction model integrating GARCH models with a distribution manipulation strategy based on LSTM networks for stock market volatility," *IEEE Access*, vol. 10, pp. 34743–34754, 2022.
[58] R. M. D. Gonzales and C. A. Hargreaves, "How can we use artificial intelligence for stock recommendation and risk management? A proposed decision support system," *Int. J. Inf. Manage. Data Insights*, vol. 2, no. 2, Nov. 2022, Art. no. 100130.
[59] I. Fafaliou, M. Giaka, D. Konstantios, and M. Polemis, "Firms' ESG reputational risk and market longevity: A firm-level analysis for the United States," *J. Bus. Res.*, vol. 149, pp. 161–177, Oct. 2022.
[60] S. Gangwar, D. Fernández, C. Pozo, R. Folgado, L. Jiménez, and D. Boer, "Scheduling optimization and risk analysis for energy-intensive industries under uncertain electricity market to facilitate financial planning," *Comput. Chem. Eng.*, vol. 174, Jun. 2023, Art. no. 108234.
[61] I. E. Ahmed, R. Mehdi, and E. A. Mohamed, "The role of artificial intelligence in developing a banking risk index: An application of adaptive neural network-based fuzzy inference system (ANFIS)," *Artif. Intell. Rev.*, early access, pp. 1–23, Apr. 2023.
[62] O. Rodríguez-Espíndola, S. Chowdhury, P. K. Dey, P. Albores, and A. Emrouznejad, "Analysis of the adoption of emergent technologies for risk management in the era of digital manufacturing," *Technol. Forecasting Social Change*, vol. 178, May 2022, Art. no. 121562.
[63] A. Taeihagh, "Governance of artificial intelligence," *Policy Soc.*, vol. 40, no. 2, pp. 137–157, 2021.
[64] A. Arslan, C. Cooper, Z. Khan, I. Golgeci, and I. Ali, "Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies," *Int. J. Manpower*, vol. 43, no. 1, pp. 75–88, Apr. 2022.
[65] P. Giudici, "FinTech risk management: A research challenge for artificial intelligence in finance," *Frontiers Artif. Intell.*, vol. 1, p. 1, Nov. 2018.
[66] B. Rezazadeh, P. Asghari, and A. M. Rahmani, "Computer-aided methods for combating COVID-19 in prevention, detection, and service provision approaches," *Neural Comput. Appl.*, vol. 35, pp. 14739–14778, May 2023.

[67] T.-I. Theodorou, A. Zamichos, M. Skoumperdis, A. Kougioumtzidou, K. Tsolaki, D. Papadopoulos, T. Patsios, G. Papanikolaou, A. Konstantinidis, A. Drosou, and D. Tzovaras, "An AI-enabled stock prediction platform combining news and social sensing with financial statements," *Future Internet*, vol. 13, no. 6, p. 138, May 2021.
[68] D. Lv, S. Yuan, M. Li, and Y. Xiang, "An empirical study of machine learning algorithms for stock daily trading strategy," *Math. Problems Eng.*, vol. 2019, pp. 1–30, Apr. 2019.
[69] D. Mhlanga, "Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment," *Int. J. Financial Stud.*, vol. 9, no. 3, p. 39, Jul. 2021.

AMIR MASOUD RAHMANI received the B.S. degree in computer engineering from Amirkabir University, Tehran, in 1996, the M.S. degree in computer engineering from the Sharif University of Technology, Tehran, in 1998, and the Ph.D. degree in computer engineering from Islamic Azad University (IAU), Tehran, in 2005. His research interests include the Internet of Things, cloud/fog computing, and evolutionary computing.

BAHAREH REZAZADEH received the B.S. degree in information technology engineering from the Urmia University of Technology, in 2013, the M.S. degree in MBA from the University of Tehran, in 2015, and the second master's degree in computer engineering from the Science and Research Branch, Islamic Azad University (IAU), Tehran, in 2022. She is currently a Senior Researcher with IAU. Her research interests include the Internet of Things, distributed computing, and artificial intelligence.

MAJID HAGHPARAST (Senior Member, IEEE) is currently a Researcher with the Faculty of Information Technology, University of Jyväskylä, Finland. He is an Associate Editor of the *Cluster Computing* (Springer) and *Journal of Computational Electronics* (Springer). He is also an Editorial Board Member of *Optical and Quantum Electronics* journal (Springer).

WEI-CHE CHANG received the bachelor's degree in information management from the National Yunlin University of Science and Technology, in 2022. He is currently pursuing the master's degree in artificial intelligence with the International Graduate Institute. His research interests include big data and the Internet of Vehicles.

SHEN GUAN TING received the associate degree in information management from the National Taipei University of Business, in 2020, and the bachelor's degree in information management from the National Yunlin University of Science and Technology, in 2022, where he is currently pursuing the degree with the International Graduate Institute of Artificial Intelligence.