SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 4, (2026), pp. 7935-7941
Open Access. Online & Print

DOI: 10.5281/zenodo.12426792

ADOPTION OF ARTIFICIAL INTELLIGENCE IN FINANCIAL MARKETS AND ITS STRATEGIES FOR INVESTMENT– A SYSTEMATIC LITERATURE REVIEW USING SCOPUS DATABASE

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Received: 16/10/2025
Accepted: 08/04/2026

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ABSTRACT

The industrial revolution has undergone a paradigm shift across various sectors worldwide. The usage of AI and other technology transformations has provided an easier way to predict the financial markets, which uses machine learning, blockchain, and various algorithms for predicting the stock markets and making investment decisions. The increasing availability of big data with advances in the power of computers has enabled the adoption of AI, emerging as an alternative model for traditional methods and techniques. The main objective on conducting Systematic Literature Review (SLR) is (i) to examine the extent of research studies carried in adoption of artificial intelligence with the investment strategies, and the applied AI techniques and evaluate on the effectiveness in financial markets, The Research analyzes the application of predictive analytics in forecasting stock markets, and to suggest directions for future research which combine AI and analyze the stock price predictions. The methodology adopted for Systematic Literature Review (SLR) is through PRISMA(Preferred Reporting Items for Systematic Reviews). The data sources are gathered from Scopus, Google Scholar, and Semantic Scholar through keyword and Boolean operations such as "Artificial Intelligence" and "Financial Markets", "Artificial Intelligence" and "Investment Strategy", "Machine Learning" and "Financial Markets". The searches are limited through the selection of articles, conference papers, book chapters, and review papers which are published from 2015 to 2025. Studies will be gathering information on the AI adoption on trading strategies and investment mechanisms, which are helpful for decision-making. The inclusion criteria are based on studies that are relevant to the application of AI and

related technologies for financial markets, studies that are presented with empirical content, a theoretical framework, and case-based approaches. The relevant studies are filtered based on the title, abstract, and keywords. The systematic literature review is based on the domination of AI techniques, Algorithmic, high trading, Prediction power, and optimization. Risk assessment and management.

KEYWORDS: Artificial Intelligence, Financial Markets, Investment Strategies, Algorithmic Trading, Portfolio Optimization.

INTRODUCTION

One of the most significant advancements in contemporary finance is the use of artificial intelligence (AI) in financial markets. The way financial institutions function has changed over the last 20 years due to the quick development of digital technology, massive data storage capacities, and sophisticated computing power. AI refers to computer programs designed to perform tasks such as learning from data, identifying patterns, making judgments, and resolving issues that often require human intelligence. Artificial intelligence (AI) is being used more and more in financial markets to analyze vast amounts of financial data, forecast market trends, manage risk, detect fraud, and assist with investment decisions.

Every second, enormous volumes of data are produced by financial markets, such as stock exchanges, bond markets, commodities markets, and foreign exchange markets. To work with such large and complex datasets, you often need to use traditional analytical methods. Because of this, banks, hedge funds, investment firms, and other financial institutions are using AI-based technology to boost their productivity, accuracy, and profits. Robotic process automation, deep learning, machine learning, and natural language processing are just a few of the AI technologies that are widely used in trading and investment management these days. Machine learning algorithms can learn from past market data and find trends that human analysts might miss. These algorithms can make better predictions as new information comes in. Deep learning models are capable of processing complex and unstructured data such as text, audio, and images, as they are designed based on the functioning of the human brain. Natural Language Processing analyzes news, articles, financial data, and social media information. This can address price fluctuation and the sentiment of the market. AI enables investors to make quick decisions with real-time information.

Artificial Intelligence detects past data to find the patterns that are highly risky. It can identify the trading activities and enable the detection of fraud or data manipulation in the market. Through reducing risk, Artificial Intelligence is able to improve stability in the financial markets. In this context, sentiment analysis plays a crucial role in the implementation of AI in financial markets. AI assesses the investor opinion in the market through financial news and social media. Investors are able to predict fluctuations in the market and can change their strategy. AI implements quantitative funds to increase performance and also assess the current market situations.

REVIEW OF LITERATURE

Khushnuma Khan and Sanaa Zafar Shaikh (2025) state that AI creates improved performance in investment portfolios through real-time database management systems, which brings a relationship between AI techniques and financial markets.

Menaama Amoawah Nkrumah (2025). Abnormal returns and volatility shocks are recorded and quantified using event-study techniques to assess both immediate and long-term effects. GARCH and EGARCH models quantify volatility persistence and asymmetric responses to negative news, while VAR models assess spillovers of breach-related shocks across correlated securities and sectors. Findings reveal that breach disclosures typically result in short-term spikes in volatility and negative abnormal returns, with more severe impacts observed in sectors that handle sensitive customer data(2

E. Kılıç, Sıtkı Sönmezer (2025). This study compares momentum-based algorithmic trading with buy-and-hold strategies in shallow markets, assessing AI's ability to exploit inefficiencies and enhance portfolio performance, and shows that while the algorithm showed slightly better performance, the results do not provide strong statistical evidence of its superiority. Hanyi Wang and R. G. Segumpan (2025) studied the social and educational effects of portfolio optimization and algorithmic trading

According to Pallavi Rai and Chandra Shekhar (2025). The aim of the research is to understand how artificial intelligence can help in portfolio management by reducing risks of volatility in the market and other issues.

Laveena T. Dharmwani and Kavita Rameshbhai Gardharia (2025). The study aims to investigate the efficiency of AI in decisions, risks. The results show AI offers more productive engagements and decision-making. Dr. Bala Senthil and Omar J. Alkhatib (2025). AI models are good in high-frequency trading situations due to their superior patterns and real-time processing. Turgud Valiyev (2025). Research adopts portfolio optimization, which gives robustness to reinforcement learning, is timely, and adaptable. P. MuruganK. S. SureshU. Parthiban(2024) AI and ML develop algorithms enables financial institutions to manage risks easily, which makes quick investment decisions

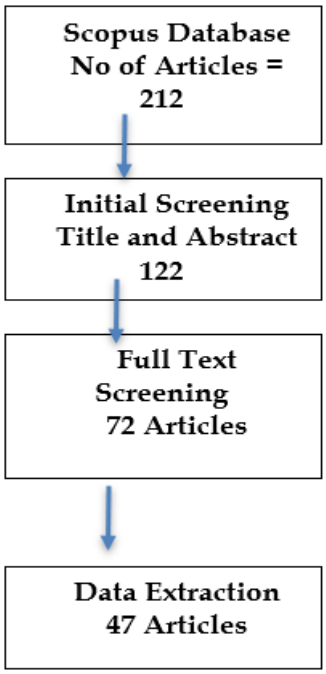
AIM OF THE RESEARCH

- To know the research carried out towards algorithmic trading for price movements and predictions.

- To identify the research on the usage of AI for portfolio optimization
- To highlight the studies towards strategies for investment.

METHODS

The study is done through a Systematic Literature Review and combined with Bibliometric analysis. The systematic review provides a comprehensive identification of relevant literature studies, and the bibliometric analysis provides a quantitative study of the publications. The research design adopted is an exploratory study. The method adopted in the PRISMA model (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) framework ensures transparency. The data sources were collected from the Scopus Database through the use of Keywords from the period of 2015 to 2026. The tools, such as VOS Viewer, are used for analyzing the bibliometric study.



ANALYSIS

USAGE OF ALGORITHMIC TRADING

The research studies in recent years have significantly contributed towards exploring computational methods to improve predictions of the stock market and the performance of trading. The majority of the studies stress machine learning, deep learning, and artificial intelligence techniques for automated trading decisions and analyze the market behavior. Indra and Supan (2025) investigated machine learning models through linear regression, Ridge regression, Random forest, and XG Boost for predicting the stock market returns in the Indonesian market. The findings show that the complex models showed slight accuracy, and other models, like ridge regression, showed better risk-adjusted performance. However, the overall performance was weak, suggesting on the short term, market movements are dominated by noise and face challenges in forecasting. Many other studies identified the specific trading strategies and the effectiveness of the technical indicators. Sukuma and Namahoot (2025) studied the technical indicators such as MA20/MA50, RSI, MACD, Bollinger Bands, and OBV through a long data set from the period 2013 to 2023. The results highlighted that multi-indicators show significant outperformance over single-indicator strategies. Corazza, Pizzi, and Marchioni (2024) proposed a trading optimizer through Particle Swarm Optimization (PSO), which optimizes the indicators' parameters, trading rules, and signals. The findings of the study suggest that multiple optimization processes enhance overall trading effectiveness. Several studies examined advanced artificial intelligence approaches such as reinforcement learning, genetic programming, and deep learning. Baltaseros and Miranda (2024) suggested reinforcement based investment strategy, such as WARL, to integrate multiobjectives reward function for better management of risk. The results showed improved performance on the financial metrics. Agarwal (2023) studies the deep reinforcement learning model to capture short-term and long-term market patterns, which improves profitability and reduces risk. Christodoulaki and Kyroppulou (2025), combining technical indicators with sentiment analysis improves trading strategy performance and highlights on the value of integrating various financial information. Some studies also addressed the challenges of technological advancements. Abdellal and Umar (2025) highlighted the lack of consensus in predictive factors and data sources that are used in stock price forecasting. Dairwish et al (2025) stated that Large Language Models, which show progress in processing complex textual data and improved financial analytics, while some studies stressed that algorithmic trading models performed well in simulations but have challenges in real-world applications. Ormos (2023) reported that AI-based trading using a support vector machine can generate abnormal returns in simulations, which can have high transaction costs. Muyateng et al (2024) AI-based fuzzy trading models can provide moderate prediction accuracy while reducing the risk.

Application of Portfolio Optimization

Portfolio optimization has become an important element of algorithmic trading with the increased usage of Artificial Intelligence, Machine Learning, and advanced data analytics. Modern portfolio theory focuses on balancing risk and return through diversification. Recent studies show the shift towards data-driven and adaptive models, which respond better to a variety of market conditions. Frolov and Bolko (2025) studied the camparision on various portfolio optimization approaches, such as MPT, Monte-Carlo, and AI-based optimization and genetic algorithms. The findings state that AI and the algorithms outperform the traditional methods in moderating risk adjusted reutrns. Mone Carlo also improves risk assessment through scenario-based modelling, which monitors risks more effectively than static financial models. The integration of reinforcement learning and natural language processing is being analyzed in recent studies. Botunac, Petkovic, and Bosna (2025) stated that automated trading combining deep reinforcement learning and natural language processing analyzes financial news and market information. It integrates transformer-based NLP with a reinforcement learning trading framework. The results show that the model achieved strong portfolio performance, which gave returns of 23.10% and a Sharpe Ratio of 1.45, which performs better than Mean Variance Model and the Dow Jones Industrial Average Benchmark. The study concluded that textual information from financial news proves a significant improvement in decision making capability of portfolio optimization systems. Recent studies explored the usage of Large Language Models and sentiment analysis to improve portfolio construction strategies. Lacovides and Zhou (2025) developed the FDPO model, which applies the Direct Preference Optimization to adopt pre-trained language models for financial sentiment analysis. The results showed that a portfolio constructed using sentiment based predicitions give positive returns and high risk-adjusted performance with high transaction costs. Mun and Kim (2025) studied that portfolio-based LLMs derived news sentiment outperformed market indices n US stock market. The results show that advanced LLMs improve portfolio performance through complex financial patterns. Reinforcement learning has also emerged as a powerful tool for portfolio management and asset allocation. Nupian (2025) examined the use of Deep Q networks (DQN) for portfolio optimization using historical data from major stocks. The results were that DQN agents are capable of generating profitable trading strategies. It also highlighted the variation in performance across assets and provided recommendations that reinforcement models need continuous improvement to adapt to changing market conditions. Wang, Pradeep, and Chen (2022) stated that reinforcement learning can optimize portfolio construction and maximize financial objectives. The findings state that reinforcement models can effectively learn trading strategies and adjust the portfolio according to the market conditions. The research studies also focus on integrating predictive analytics with portfolio construction techniques. Nafia, Yousif, and Echaaou (2023) suggested a portfolio management framework that uses a neural network for predicting stock returns and the construction of a neural market portfolio. This involves predicting returns through various financial indicators and ranking stocks that determine long and short positions. The results stated that LSTM based portfolio's consistently outperformed market benchmarks, through various data sources such as technical indicators, fundamental indicators, and sector data were included in the model. Several studies examined optimization algorithms to improve portfolio decision-making. Ospina – Holguin and Padilla – Ospina (2025) developed a reinforcement learning model that is designed to maximise alpha in market timing strategies by combining multiple trading signals. This model integrated a large number of moving average signals and used principal component analysis, which reduces dimensionality while maintaining predictive power. The algorithm has brought strong performance in risk-adjusted returns. Corazza, Pizzi e Marchioni (2024). Particle Swarm Optimization, which optimizes trading signals and technical indicatorswhich improvises trading performance. Studies related to online portfolio selection have also been taken as a method for managing investments in dynamic markets. He, Yin, and Peng(2023) present an online trading algorithm called WASA and an associated portfolio strategy known as WASC. This model summarizes expert trading advice and minimizes transaction costs through selectively adjusting asset positions.

Studies on AI in Investment Strategy

Research studies show the growing integration of Artificial Intelligence (AI) techniques in investment strategies in the prediction of stock markets, portfolio optimization, and automated financial decision-making. Advanced approaches studied by Luo et al. (2025) introduced the NGNN SCRC framework for movement prediction and portfolio selection. The

model combines a semantic company relationship graph and neural networks. This improves the understanding of the influences of companies in the market. The empirical findings show that the framework outperforms existing benchmark models and produces risk-adjusted returns. The findings suggest that public information in the US equity market is not reflected in prices. Natural Language Processing (NLP) has also become an important tool for investment analytics. Cal (2025) studied on NLP facilitated predictive analytics, which enhances portfolio optimization for ultra-high-net-worth (UNHW) investors during volatile market conditions. Through sentiment analysis and traditional quantitative risk models, it provides deeper insights into investor preferences and market sentiment. The research has shown great improvements in risk-adjusted performance with a ratio of 1.37 compared to 0.74, which are obtained from the traditional Markowitz Portfolio Optimization Model. Reinforcement Learning also helps in automated investment decision-making. Xu(2024) has suggested a WARL investment strategy that replaces human decision-making in the Weighted Average Algorithm (WAA) through a reinforcement agent. The findings could be further improved by incorporating additional market information on sentiment data and financial indicators to enhance the state representation of the learning agent. Yang et al (2024) developed a deep reinforcement model using a transformer and U-net architecture to learn stock market strategies. This model integrates a multihead attention mechanism to capture both long term and short-term market patterns. The results indicate that the model can generate high profits and also maintain lower volatility compared to traditional approaches. Deep learning methods have also been applied in portfolio construction and investment decisions. Barbero et al (2024) suggest that deep learning improves the selection of a portfolio that identifies the patterns of data. Hong et al. (2023) investigated how uncertainty reduction strategies influence investors' intentions to use robo–advisor services. The research shows that factors influence investors' intentions which uses rob-advisor services. Many studies emphasize the importance of reliability in the implementation of AI financial advisory applications.

RESULTS AND DISCUSSIONS

Studies show that the application of AI models can enhance the performance of investment. It enhanced prediction capacity, which is useful for risk management and constructing portfolios effectively. The results suggest that complex learning models create higher prediction accuracy, while ridge regression has greater risk-adjusted performance. The overall prediction still remains weak and suggests that short-term movements are influenced by market noise and unprecedented factors. The results show that the optimization algorithm brings overall effectiveness in trading strategies and improves signal accuracy and decision-making.

Researches which focused on technical trading strategies states that combining multiple indicators improves trading results. Sukuma and Namahoot (2025) used multiple technical indicators, which outperformed single indicator strategies. Some studies also witnessed results on the overall effectiveness of trading strategies by improving signal accuracy and decision efficiency.

Advanced AI models, such as Reinforcement Learning and Deep Learning, have shown better results on automated trading systems. Some studies proposed reinforcement-based investment strategy Studies proposed reinforcement-based investment helped to enhance the investment strategy, which integrates multiobjective reward functions for effective risk management. Some studies have combined technical indicators with Sentiment analysis improves performance of trading strategies. However, some studies have limitations of algorithmic trading models. There is no consensus on the predictive factors or stock price forecasting. Ormnos (2023) found that AI-based trading systems have abnormal returns and also incur high transaction costs. Recent studies also explored reinforcement learning and Natural Language Processing (NLP) in portfolio management. Large Language models and sentiment analysis are also applied for portfolio construction. Studies also prove that reinforcement techniques show potential in asset allocation and portfolio management. Thus, the various results indicate that AI based nvestment strategies enhance algorithmic trading and portfolio optimization, which improves prediction accuracy, incorporates multiple data sources, and enables adaptive decision making.

CONCLUSION

A Systematic Literature Review states that the use of AI in financial markets brings about a transformation in investment strategies. The reviews depict that AI models such as Machine Learning, Deep Learning, Reinforcement Learning, and NLP have performed efficiently in algorithmic trading, portfolio optimization, and financial decisions. The research carried out enables investors and financial

investors to evaluate large amounts of data and also to respond quickly to changing market conditions. Thus implementation of AI has improved the accuracy of risk assessment and also accelerates performance of portfolios. Some of the ideas have challenges in terms of uncertainty of markets, transaction costs, and real-time AI systems. Some researchers also have ethical issues with the transparency of algorithms, and also regulatory framework needs to be fixed in developing a sustainable model of AI application for financial markets. Further research is important on the improvement of efficiency systems for AI in financial markets for operating in dynamic environments.

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