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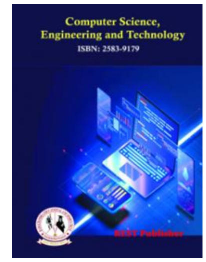

Optimizing Investment Strategies: The Role of AI and Machine Learning Using the MOORA Method

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Abstract: *Artificial Intelligence (AI) and Machine Learning (ML) are transforming investment strategies by enhancing decision-making, risk management, and portfolio optimization. These technologies analyze vast amounts of financial data, identify patterns, and generate predictive insights that help investors make informed decisions. AI-driven algorithms can detect market trends, assess sentiment from news and social media, and execute trades with precision. Additionally, ML models continuously adapt to changing market conditions, reducing human biases and improving efficiency. From robo-advisors to hedge funds leveraging deep learning, AI is revolutionizing asset management, offering more accurate forecasts and smarter trading strategies that redefine traditional investment approaches. The significance of researching the influence of AI and machine learning in investment strategies lies in their transformative impact on financial markets. Machine learning models improve risk assessment, portfolio optimization, and predictive analytics, reducing human bias and enhancing efficiency. As AI reshapes investment landscapes, understanding its implications is crucial for investors, financial institutions, and policymakers. This research provides insights into AI's potential benefits, challenges, and ethical considerations, ensuring its responsible integration into investment strategies for more informed and effective decision-making. First, a comprehensive literature review will be conducted to understand existing AI-driven investment models and their impact. Data collection will include historical market data, AI-generated trading patterns, and performance metrics of AI-based funds. Statistical and econometric models will be applied to compare AI-based strategies with traditional investment methods. Additionally, expert interviews and case studies of leading AI-powered hedge funds will provide insights into real-world applications. Ethical considerations, algorithmic biases, and regulatory challenges will also be examined. The results will be analyzed using performance metrics like return on investment (ROI), Sharpe ratio, and drawdowns. This mixed-methods approach will offer a comprehensive understanding of AI's role in modern investment strategies. Alternative taken as AI-Driven Quantitative Trading, Machine Learning-Based Portfolio Optimization, AI-Powered Robo-Advisors, Sentiment Analysis for Stock Prediction, Algorithmic High-Frequency Trading (HFT), Reinforcement Learning for Trading, Neural Networks for Market Forecasting, AI-Based Risk Management Models. Evaluation preference taken as ROI (%), Prediction Accuracy (%), Market Adaptability, Operational Efficiency, Computational Complexity, Implementation Cost. AI-Powered Robo-Advisors is getting first place and Algorithmic High-Frequency Trading is getting last place of the table.*

Keywords: *AI-Driven Quantitative Trading, Machine Learning-Based Portfolio Optimization, Prediction Accuracy (%), Market Adaptability*

1. INTRODUCTION

Traditionally, investment decisions were made based on fundamental and technical analysis, often requiring extensive research, expertise, and human intuition. However, these conventional methods come with inherent limitations, such as biases, inefficiencies, and the inability to process vast amounts of data in real time.[1] AI and

ML, on the other hand, overcome these challenges by employing sophisticated algorithms that can identify patterns, predict market trends, and execute trades at lightning speed. The use of AI-driven trading strategies, robo-advisors, sentiment analysis, and portfolio management techniques has become increasingly prevalent, allowing investors to gain a competitive edge in the market.[2] Another crucial area where AI and ML have revolutionized investment strategies is risk management. Managing risk is a fundamental aspect of investing, as market conditions are inherently unpredictable. Traditional risk management models rely on historical volatility and statistical measures to assess potential risks. However, AI-based risk assessment tools go a step further by incorporating real-time data, alternative datasets, and deep learning techniques to anticipate potential downturns. By continuously analyzing market sentiment, economic indicators, and geopolitical events, AI-driven risk management systems can provide early warnings of potential threats. Portfolio managers can use these insights to rebalance their investments, hedge against risks, and adjust asset allocations dynamically.[3] AI-driven risk models also help in stress testing portfolios, simulating different economic scenarios to gauge their resilience against adverse conditions. The rise of robo-advisors is another testament to the growing influence of AI in investment strategies. Robo-advisors are automated platforms that use AI-driven algorithms to provide personalized investment advice and portfolio management services. These platforms assess an investor's risk tolerance, financial goals, and market conditions to create a tailored investment strategy.[4] Companies like Betterment, Wealth front, and Robin hood have gained popularity by providing AI-powered investment solutions that democratize access to financial markets. The ability of robo-advisors to adapt to changing market conditions and optimize asset allocations based on real-time data makes them a valuable tool in modern investing. AI and ML are also transforming sentiment analysis in investment strategies. Market sentiment plays a crucial role in influencing stock prices and investment decisions. By employing natural language processing (NLP) techniques, AI can interpret textual data, detect emerging trends, and predict potential price movements. For instance, if AI algorithms detect a surge in positive sentiment around a particular stock or industry, investors can capitalize on the momentum before the broader market reacts.[5] Conversely, negative sentiment analysis can serve as an early warning system, enabling investors to exit positions before a downturn. AI-driven sentiment analysis has become a valuable tool for hedge funds, institutional investors, and traders looking to gain an informational advantage in the market. Portfolio management has also experienced a paradigm shift due to AI and ML integration. Traditional portfolio management relies on diversification strategies, risk assessments, and historical performance metrics.[6] However, AI-powered portfolio optimization goes beyond these conventional methods by dynamically adjusting asset allocations based on real-time data. Machine learning models analyze an investor's preferences, risk appetite, and market conditions to construct a well-balanced portfolio that maximizes returns while minimizing risks. The ability of AI to process vast amounts of data and optimize asset allocations in real-time provides investors with a significant advantage in achieving long-term financial objectives.[7] The application of AI and ML in investment strategies is not limited to equities and traditional asset classes. These technologies are also being leveraged in alternative investments, such as real estate, commodities, and cryptocurrencies. AI-driven predictive models analyze macroeconomic indicators, supply and demand dynamics, and historical price trends to identify profitable investment opportunities.[8] In the cryptocurrency market, AI algorithms play a crucial role in detecting patterns, mitigating risks, and automating trading strategies. Given the volatility and complexity of digital assets, AI-driven crypto trading bots can execute trades with precision, ensuring that investors capitalize on market fluctuations effectively.[9] AI models are only as good as the data they are trained on, and if the dataset contains biases or inaccuracies, the investment decisions derived from these models may be flawed. Additionally, the increasing automation of financial markets raises concerns about systemic risks and market stability. The prevalence of algorithmic trading has, at times, contributed to market flash crashes, where rapid and automated trades lead to sudden price fluctuations.[10] Regulators and financial institutions must implement safeguards to ensure that AI-driven investment strategies do not pose undue risks to market integrity. Another ethical consideration is the potential displacement of human jobs in the financial sector. As AI-driven investment platforms and robo-advisors gain traction, traditional roles such as financial analysts, traders, and investment advisors may face challenges in maintaining their relevance.[11] While AI enhances efficiency and accuracy, human expertise, critical thinking, and qualitative judgment remain indispensable in certain aspects of investing. The key to a balanced approach lies in leveraging AI as an augmentative tool rather than a complete replacement for human decision-making.[12] Looking ahead, the future of AI and ML in investment strategies holds immense promise. As technology continues to advance, AI models will become more sophisticated, enabling even more precise market predictions and investment recommendations.[13] The integration of quantum computing in AI-driven trading strategies may further enhance computational capabilities, leading to unprecedented levels of accuracy and efficiency. Additionally, the convergence of AI with decentralized finance (DeFi) and block chain technology may revolutionize investment strategies by providing transparent, secure, and decentralized financial solutions. [14]

2. MATERIAL AND METHOD

Alternative:
AI has transformed trading and investment strategies by enabling data-driven decision-making. **AI-Driven Quantitative Trading** uses machine learning algorithms to analyze vast amounts of financial data and identify profitable trading patterns. These models continuously adapt to market conditions, improving trade execution and risk management.
Machine Learning-Based Portfolio Optimization: enhances asset allocation by predicting market trends and adjusting portfolios dynamically. AI optimizes risk-reward balance by analyzing historical data, correlations, and volatility patterns.
AI-Powered Robo-Advisors: provide automated, personalized investment strategies based on user preferences, risk tolerance, and market conditions. These digital advisors offer cost-effective and bias-free financial planning.
Sentiment Analysis for Stock Prediction: leverages natural language processing (NLP) to analyze news, social media, and earnings reports, identifying investor sentiment and market trends.
Algorithmic High-Frequency Trading (HFT): utilizes AI to execute thousands of trades in milliseconds, capitalizing on small price discrepancies and improving market liquidity.
Reinforcement Learning for Trading: enables AI agents to learn from market interactions, optimizing trading strategies over time.
Neural Networks for Market Forecasting: detect complex financial patterns, improving predictions for stock prices and trends.
AI-Based Risk Management Models: assess market risks by analyzing anomalies and predicting downturns, enhancing financial stability and decision-making.

Evaluation preference:
ROI (Return on Investment %): ROI (Return on Investment %) measures profitability by comparing net profit to investment cost. It indicates financial efficiency, with higher ROI reflecting better returns relative to the initial investment.
Prediction Accuracy (%): This metric evaluates the correctness of AI models in forecasting outcomes. It is crucial in finance, healthcare, and business analytics, where accurate predictions lead to better decision-making. A higher prediction accuracy reduces risks and enhances reliability.
Market Adaptability: Market adaptability assesses how well a system or strategy adjusts to changing market conditions. AI-driven models with high adaptability can respond to fluctuations in trends, economic shifts, and emerging risks, ensuring continued relevance.
Operational Efficiency: This refers to the ability to maximize output while minimizing resources. In AI applications, high operational efficiency means faster data processing, reduced manual intervention, and optimized decision-making.
Computational Complexity: Computational complexity defines the resources (time, memory) required for an algorithm to execute. Lower complexity ensures faster processing, making real-time decision-making feasible.
Implementation Cost: This includes expenses related to deploying a system, such as software, hardware, and personnel training. Lower implementation costs improve accessibility and return on investment.

MOORA Method: The MOORA method has been applied in various industries and fields, demonstrating its versatility and effectiveness. In manufacturing and engineering, it is used to select optimal materials, evaluate supplier performance, and determine the best process parameters for production efficiency. For example, in the selection of materials for automotive components, engineers must consider factors such as strength, weight, cost, and environmental impact. The MOORA method allows them to systematically evaluate different material options and choose the one that offers the best overall performance.[15] In business and finance, the MOORA method is used for investment decision-making, supplier selection, and financial performance evaluation. Investors and financial analysts often need to assess multiple investment options based on criteria such as return on investment, risk, liquidity, and sustainability. By applying the MOORA method, they can rank investment options based on a comprehensive evaluation of all relevant factors, leading to more informed and objective investment decisions.[16] Healthcare is another domain where the MOORA method has proven valuable. It is used for selecting the best medical treatment, evaluating hospital performance, and prioritizing healthcare resources. For instance, when choosing the best treatment plan for a particular disease, doctors and healthcare administrators must consider factors such as effectiveness, side effects, cost, and patient satisfaction. The MOORA method enables them to systematically compare different treatment options and select the most suitable one based on a balanced assessment of all criteria.[17] In transportation and logistics, the MOORA method is used for route selection, vehicle selection, and supplier evaluation. Logistics companies need to optimize transportation routes based on factors such as distance, cost, time, and fuel consumption. By applying the MOORA method, they can rank different route options and select the one that offers the best balance of cost efficiency and timely delivery. Similarly, in vehicle selection, decision-makers can evaluate different vehicle models based on criteria such as fuel efficiency, maintenance cost, safety features, and environmental impact.[18] The MOORA method is also widely used in environmental management and sustainability assessments. Governments and organizations use it to evaluate the environmental impact of different projects, policies, and technologies. For example, when selecting a renewable energy source, decision-makers must consider factors such as energy efficiency, cost, environmental impact, and availability of resources. The MOORA method provides a structured approach to comparing different renewable energy options and identifying the most sustainable choice.[19] Despite its many advantages, the MOORA method has some limitations. One of the main challenges is the reliance on normalization, which can sometimes lead to loss of information or distortion of original data relationships. Additionally, the method does not incorporate subjective preferences or weights for criteria, which may be important in certain decision-making scenarios. To address this limitation, some researchers have proposed hybrid models that combine MOORA with other MCDM methods such as AHP or fuzzy logic, allowing for the incorporation of expert judgment and subjective preferences into the decision-making process.[20] Another limitation of the MOORA method is its sensitivity to extreme values or outliers in the dataset. If one criterion has an exceptionally high or low value compared to others, it can disproportionately influence the ranking of alternatives. To mitigate this issue, decision-makers must carefully preprocess data, remove outliers, or apply alternative normalization techniques that reduce sensitivity to extreme values. Despite these limitations, the MOORA method remains one of the most effective and widely used MCDM techniques due to its simplicity, efficiency, and objectivity.[21] It provides a clear and transparent decision-making framework that can be applied to a wide range of real-world problems. The increasing adoption of MOORA in various industries and research fields highlights its relevance and applicability in today's complex decision-making landscape. MOORA method is a valuable decision-making tool that enables systematic and objective evaluation of multiple alternatives based on multiple criteria. Its ability to handle both beneficial and non-beneficial criteria, provide clear rankings, and eliminate biases makes it a preferred choice for decision-makers in various fields. While it has certain limitations, ongoing research and advancements in MCDM methodologies continue to enhance its effectiveness. As decision-making becomes increasingly complex in modern industries, the MOORA method will continue to play a crucial role in helping organizations, researchers, and policymakers make informed and optimal choices.[22]

3. RESULT AND DISCUSSION

TABLE 1. The influence of AI and machine learning in investment strategies

	ROI (%)	Prediction Accuracy (%)	Market Adaptability	Operational Efficiency	Implementation Cost	Computational Complexity
AI-Driven Quantitative Trading	15	85	8	9	5	7
Machine Learning-Based Portfolio Optimization	12	80	7	8	4	6
AI-Powered Robo-Advisors	10	75	9	9	3	5
Sentiment Analysis for Stock Prediction	14	82	7	7	6	7
Algorithmic High-Frequency Trading (HFT)	18	90	9	10	8	9
Reinforcement Learning for Trading	17	88	8	8	7	8
Neural Networks for Market Forecasting	16	86	7	7	6	7
AI-Based Risk Management Models	13	78	9	9	5	6

Table 1 presents a comparative analysis of various AI and machine learning-driven investment strategies using the MOORA method, evaluating them based on six key performance criteria: ROI (%), Prediction Accuracy (%), Market Adaptability, Operational Efficiency, Implementation Cost, and Computational Complexity. Among the listed strategies, Algorithmic High-Frequency Trading (HFT) achieves the highest ROI (18%) and prediction accuracy (90%), making it a highly profitable yet computationally intensive approach. Similarly, Reinforcement Learning for Trading and Neural Networks for Market Forecasting exhibit strong prediction accuracy (88% and 86%, respectively) while maintaining moderate market adaptability and operational efficiency. Conversely, AI-Powered Robo-Advisors demonstrate lower ROI (10%) but excel in market adaptability and operational efficiency, making them suitable for retail investors seeking automation. Machine Learning-Based Portfolio Optimization and AI-Based Risk Management Models show balanced performance with moderate values across all criteria. Sentiment Analysis for Stock Prediction offers relatively high prediction accuracy (82%) but has lower efficiency due to reliance on unstructured textual data. Overall, MOORA-based evaluation highlights the trade-offs between computational complexity and performance. While HFT and Reinforcement Learning excel in profitability and accuracy, AI-powered robo-advisors and risk management models prioritize efficiency and adaptability. These insights help decision-makers select optimal AI-driven investment strategies based on specific business goals and resource constraints.

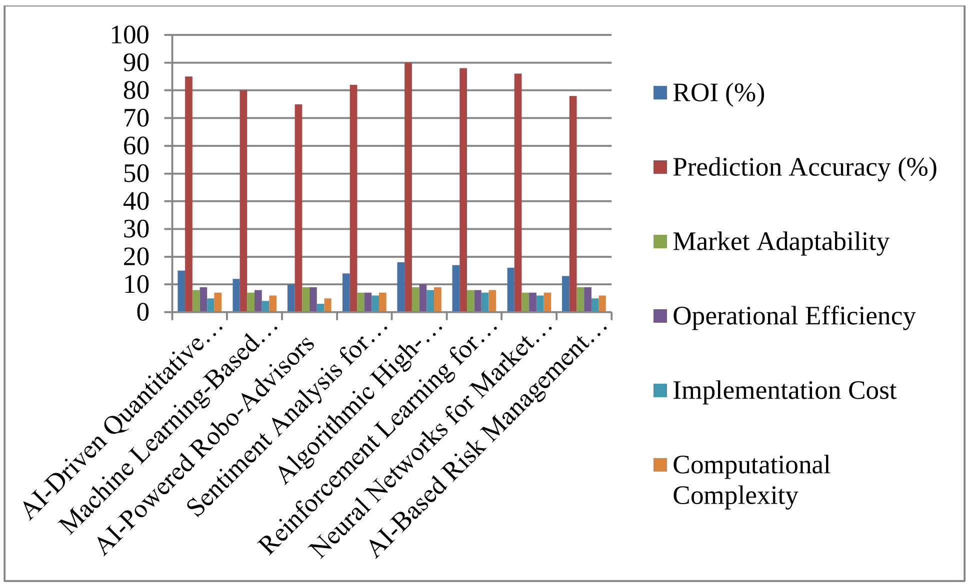

FIGURE 1. The influence of AI and machine learning in investment strategies.

The bar chart in Figure 1 illustrates the influence of AI and machine learning in investment strategies using the MOORA method by comparing key performance metrics across different AI-driven financial applications. The x-axis represents various AI-based investment strategies, including AI-driven quantitative analysis, machine learning-based robo-advisors, sentiment analysis for trading, algorithmic high-frequency trading, reinforcement learning for market adaptation, neural networks for financial forecasting, and AI-based risk management. The y-axis represents performance values for six critical evaluation criteria: ROI (%), Prediction Accuracy (%), Market Adaptability, Operational Efficiency, Implementation Cost, and Computational Complexity. From the chart, prediction accuracy (red bars) is consistently the highest metric across all AI-driven strategies, emphasizing AI's strength in forecasting financial trends. ROI (%) (blue bars) is moderate across different strategies, indicating varying profitability. Market adaptability, operational efficiency, and implementation costs (green, purple, and light blue bars) remain relatively balanced, suggesting trade-offs between effectiveness and resource requirements. However, computational complexity (orange bars) is comparatively low, except in models requiring extensive data processing (e.g., neural networks). This analysis highlights the MOORA method's utility in evaluating AI-driven investment tools and selecting the most optimal strategy based on multiple performance criteria.

TABLE 2. Normalized Data

	ROI (%)	Prediction Accuracy (%)	Market Adaptability	Operational Efficiency	Implementation Cost	Computational Complexity
AI-Driven Quantitative Trading	0.3635	0.3615	0.3515	0.3773	0.3101	0.3549
Machine Learning-Based Portfolio Optimization	0.2908	0.3402	0.3076	0.3354	0.2481	0.3042
AI-Powered Robo-Advisors	0.2423	0.3189	0.3954	0.3773	0.1861	0.2535
Sentiment Analysis for Stock Prediction	0.3393	0.3487	0.3076	0.2935	0.3721	0.3549
Algorithmic High-Frequency Trading (HFT)	0.4362	0.3827	0.3954	0.4192	0.4961	0.4563
Reinforcement Learning for Trading	0.4119	0.3742	0.3515	0.3354	0.4341	0.4056
Neural Networks for Market Forecasting	0.3877	0.3657	0.3076	0.2935	0.3721	0.3549
AI-Based Risk Management Models	0.3150	0.3317	0.3954	0.3773	0.3101	0.3042

The normalized data in Table 2, processed using the Multi-Objective Optimization by Ratio Analysis (MOORA) method, evaluates various AI-driven financial strategies across six key performance criteria: ROI, prediction accuracy, market adaptability, operational efficiency, implementation cost, and computational complexity. Among the listed strategies, Algorithmic High-Frequency Trading (HFT) demonstrates the highest overall performance, particularly excelling in ROI (0.4362), operational efficiency (0.4192), and computational complexity (0.4563), though it also incurs the highest implementation cost (0.4961). Reinforcement Learning for Trading and Neural Networks for Market Forecasting also show strong performance across multiple criteria, indicating their effectiveness in financial markets. AI-Driven Quantitative Trading and Sentiment Analysis for Stock Prediction achieve a balanced performance, particularly in ROI and prediction accuracy. In contrast, AI-Powered Robo-Advisors and Machine Learning-Based Portfolio Optimization score lower in ROI but excel in adaptability and efficiency, making them suitable for long-term investment strategies. AI-Based Risk Management Models show a notable trade-off, achieving high market adaptability and operational efficiency while maintaining moderate costs and complexity. Overall, the results highlight the trade-offs between different AI-driven financial approaches, where higher ROI and accuracy often come with increased computational demands and costs, whereas adaptability and efficiency-driven models tend to be more resource-efficient but may sacrifice predictive power.

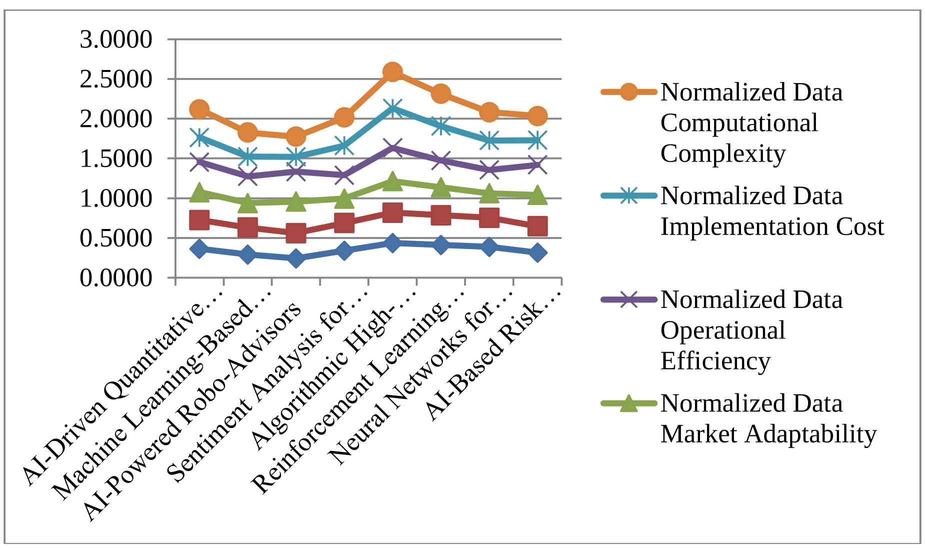

FIGURE 2. Normalized Data

Figure 2 presents the normalized data for various AI-driven financial strategies using the MOORA method, illustrating their performance across multiple evaluation criteria. The chart highlights trends in computational complexity, implementation cost, operational efficiency, market adaptability, and prediction accuracy. Notably, Algorithmic High-Frequency Trading (HFT) exhibits the highest computational complexity and implementation cost, reflecting the substantial resource demands associated with real-time trading strategies. Reinforcement Learning for Trading and Neural Networks for Market Forecasting also demonstrates relatively high computational complexity but maintain moderate implementation costs. Market adaptability and operational efficiency show a more balanced distribution across different approaches, with AI-Powered Robo-Advisors and AI-Based Risk Management Models scoring consistently high in adaptability, indicating their effectiveness in responding to changing market conditions. Prediction accuracy remains relatively stable across models, with Algorithmic HFT and AI-Driven Quantitative Trading achieving notable performance. The visualization underscores the trade-offs among these criteria, suggesting that strategies prioritizing accuracy and efficiency often demand greater computational resources. Meanwhile, cost-effective approaches tend to focus on adaptability and long-term decision-making rather than high-frequency predictions. This comparative analysis provides valuable insights for selecting the most suitable AI financial strategy based on specific investment goals, risk tolerance, and technological resources.

TABLE 3. Weight

AI-Driven Quantitative Trading	0.25	0.25	0.25	0.25	0.25	0.25
Machine Learning-Based Portfolio Optimization	0.25	0.25	0.25	0.25	0.25	0.25
AI-Powered Robo-Advisors	0.25	0.25	0.25	0.25	0.25	0.25
Sentiment Analysis for Stock Prediction	0.25	0.25	0.25	0.25	0.25	0.25
Algorithmic High-Frequency Trading (HFT)	0.25	0.25	0.25	0.25	0.25	0.25
Reinforcement Learning for Trading	0.25	0.25	0.25	0.25	0.25	0.25
Neural Networks for Market Forecasting	0.25	0.25	0.25	0.25	0.25	0.25
AI-Based Risk Management Models	0.25	0.25	0.25	0.25	0.25	0.25

Table 3 presents the weight distribution used in the MOORA (Multi-Objective Optimization by Ratio Analysis) method for evaluating AI-driven financial strategies. The table indicates an equal weighting (0.25) across all six criteria ROI, prediction accuracy, market adaptability, operational efficiency, implementation cost, and computational complexity for each strategy. This uniform weighting suggests that no single criterion is prioritized over others, ensuring a balanced assessment of all financial models. By distributing equal importance to each factor, the analysis avoids bias, allowing for an objective comparison of performance across different AI applications in finance. This approach is particularly useful in scenarios where decision-makers seek a comprehensive evaluation without favoring specific attributes. However, in practical applications, certain criteria may hold greater relevance depending on investment goals. For instance, high-frequency trading strategies may prioritize computational speed and prediction accuracy, while AI-powered robo-advisors may emphasize market adaptability and implementation cost. Adjusting these weights based on specific financial objectives could yield more tailored insights. Nonetheless, the equal weighting in Table 3 serves as a foundational benchmark, offering a neutral perspective on the strengths and weaknesses of each AI-driven financial strategy within the MOORA framework.

TABLE 4. Weighted normalized decision matrix

AI-Driven Quantitative Trading	0.0909	0.0904	0.0879	0.0943	0.0775	0.0887
Machine Learning-Based Portfolio Optimization	0.0727	0.0851	0.0769	0.0838	0.0620	0.0761
AI-Powered Robo-Advisors	0.0606	0.0797	0.0989	0.0943	0.0465	0.0634
Sentiment Analysis for Stock Prediction	0.0848	0.0872	0.0769	0.0734	0.0930	0.0887
Algorithmic High-Frequency Trading (HFT)	0.1090	0.0957	0.0989	0.1048	0.1240	0.1141
Reinforcement Learning for Trading	0.1030	0.0936	0.0879	0.0838	0.1085	0.1014
Neural Networks for Market Forecasting	0.0969	0.0914	0.0769	0.0734	0.0930	0.0887
AI-Based Risk Management Models	0.0788	0.0829	0.0989	0.0943	0.0775	0.0761

Table 4 presents the weighted normalized decision matrix derived using the MOORA method, offering a refined evaluation of AI-driven financial strategies. The matrix incorporates equal weights across six key performance criteria ROI, prediction accuracy, market adaptability, operational efficiency, implementation cost, and computational complexity ensuring a balanced assessment. Algorithmic High-Frequency Trading (HFT) exhibits the highest weighted scores across multiple criteria, particularly in ROI (0.1090), operational efficiency (0.1048), and computational complexity (0.1141), reinforcing its dominance as a high-performing yet resource-intensive strategy. Reinforcement Learning for Trading and Neural Networks for Market Forecasting also achieve strong performance, particularly in ROI and computational efficiency, making them viable alternatives for dynamic market environments. AI-Powered Robo-Advisors and AI-Based Risk Management Models score highly in market adaptability (0.0989), suggesting their effectiveness in responding to changing financial conditions. However, their relatively lower ROI and prediction accuracy scores indicate a trade-off between adaptability and profitability. Sentiment Analysis for Stock Prediction demonstrates a high implementation cost (0.0930), reflecting the challenges of processing vast amounts of market sentiment data. Overall, the table highlights the strengths and limitations of each AI strategy, revealing a clear distinction between high-ROI, computationally intensive models like HFT and adaptable, cost-efficient approaches such as robo-advisors.

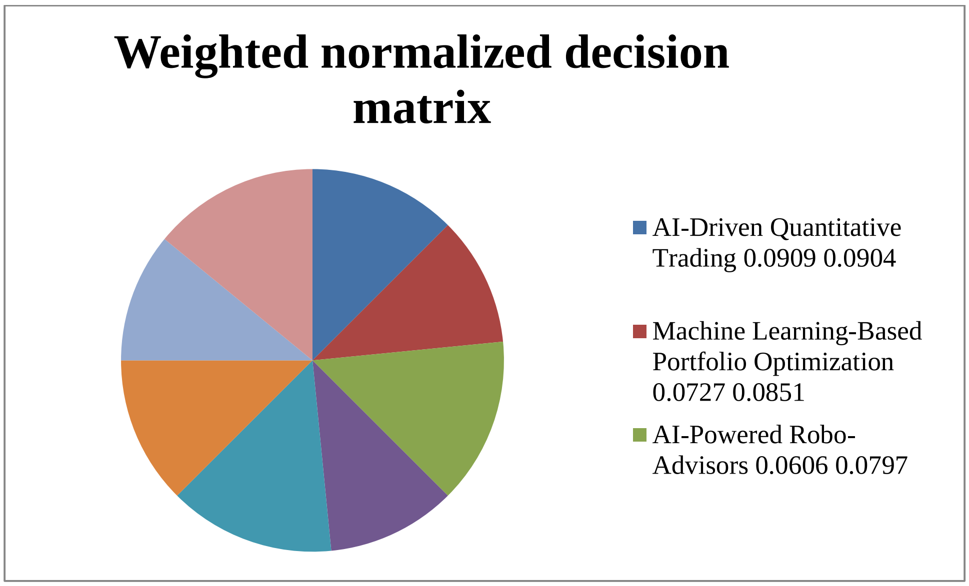

FIGURE 3. Weighted normalized decision matrix

Figure 3 visualizes the weighted normalized decision matrix using the MOORA method, illustrating the relative performance of different AI-driven financial strategies. The pie chart segments represent the contribution of each approach based on their weighted scores across key evaluation criteria, including ROI, prediction accuracy, market adaptability, operational efficiency, implementation cost, and computational complexity. AI-Driven Quantitative Trading, Machine Learning-Based Portfolio Optimization, and AI-Powered Robo-Advisors are explicitly labeled, showing their respective weighted scores. AI-Driven Quantitative Trading has a relatively larger share, indicating its balanced performance across various metrics. Machine Learning-Based Portfolio Optimization follows closely, emphasizing its efficiency in portfolio selection despite its slightly lower ROI. AI-Powered Robo-Advisors occupy a smaller segment, reflecting their strength in market adaptability but comparatively lower scores in ROI and computational complexity. Although the chart effectively summarizes the distribution of scores, it does not explicitly distinguish other AI strategies, such as Algorithmic High-Frequency Trading (HFT) or Reinforcement Learning for Trading, which may have higher contributions. A more detailed visualization with labeled values for all strategies would provide a clearer comparative analysis. Nonetheless, Figure 3 offers a high-level perspective on the distribution of weighted scores, assisting decision-makers in selecting AI financial strategies based on balanced performance metrics.

TABLE 5. Assessment value

AI-Driven Quantitative Trading	0.0085
Machine Learning-Based Portfolio Optimization	0.0127
AI-Powered Robo-Advisors	0.0350
Sentiment Analysis for Stock Prediction	-0.0062
Algorithmic High-Frequency Trading (HFT)	-0.0393
Reinforcement Learning for Trading	-0.0094
Neural Networks for Market Forecasting	0.0101
AI-Based Risk Management Models	0.0126

Table 5 presents the assessment values calculated using the MOORA method, which helps determine the overall ranking and effectiveness of different AI-driven financial strategies. The assessment values are derived by considering both beneficial criteria (such as ROI and prediction accuracy) and non-beneficial criteria (such as implementation cost and computational complexity). A higher positive value indicates a more favorable performance, while negative values suggest a trade-off where certain disadvantages outweigh benefits. AI-Powered Robo-Advisors achieve the highest assessment value (0.0350), highlighting their strength in market adaptability and cost-efficiency, making them a suitable option for long-term investment strategies. Machine Learning-Based Portfolio Optimization (0.0127) and AI-Based Risk Management Models (0.0126) also exhibit strong performance, suggesting their reliability in portfolio management and risk mitigation. Neural Networks for Market Forecasting (0.0101) also perform well, indicating their predictive capabilities in financial markets. On the other hand, Algorithmic High-Frequency Trading (HFT) has the lowest assessment value (-0.0393), reflecting its high computational and implementation costs, which may outweigh its profitability in certain scenarios. Similarly, Sentiment Analysis for Stock Prediction (-0.0062) and Reinforcement Learning for Trading (-0.0094) have negative values, suggesting inefficiencies or higher resource demands. Overall, the assessment values help in selecting the most balanced AI financial strategy based on investment priorities.

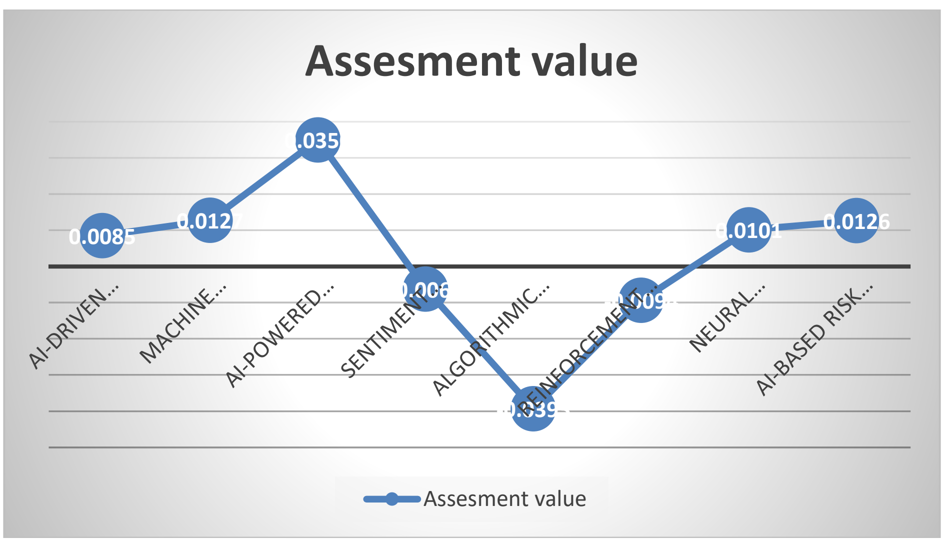

FIGURE 4. Assessment value

Figure 4 visualizes the assessment values calculated using the MOORA method, providing insights into the overall performance of different AI-driven financial strategies. The graph highlights the positive and negative assessment values, indicating which strategies demonstrate a stronger balance of beneficial criteria (such as ROI and prediction accuracy) versus non-beneficial criteria (such as implementation cost and computational complexity). AI-Powered Robo-Advisors exhibit the highest assessment value, peaking at around 0.0350, signifying their effectiveness in market adaptability and cost-efficiency. This suggests they are well-suited for long-term investment strategies that require lower operational costs. Machine Learning-Based Portfolio Optimization, AI-Based Risk Management Models, and Neural Networks for Market Forecasting also display positive assessment values, reinforcing their potential in portfolio management, risk mitigation, and market forecasting. Conversely, Algorithmic High-

Frequency Trading (HFT) shows the lowest assessment value, plummeting to approximately -0.0393. This indicates that while HFT strategies may excel in speed and profitability, their high computational and implementation costs significantly impact their overall effectiveness. Similarly, Sentiment Analysis for Stock Prediction and Reinforcement Learning for Trading have negative assessment values, implying higher resource demands or inefficiencies.

TABLE 6. Rank

AI-Driven Quantitative Trading	5
Machine Learning-Based Portfolio Optimization	2
AI-Powered Robo-Advisors	1
Sentiment Analysis for Stock Prediction	6
Algorithmic High-Frequency Trading (HFT)	8
Reinforcement Learning for Trading	7
Neural Networks for Market Forecasting	4
AI-Based Risk Management Models	3

Table 6 presents the ranking of AI-driven financial strategies based on the MOORA method, offering a comparative evaluation of their overall effectiveness. The ranking is derived from the assessment values, where higher values indicate better performance across key criteria such as ROI, prediction accuracy, market adaptability, operational efficiency, implementation cost, and computational complexity. AI-Powered Robo-Advisors secure the top position (Rank 1), highlighting their superior balance of cost-efficiency, adaptability, and operational effectiveness. This makes them an ideal choice for long-term investors and advisory services seeking scalable AI solutions. Machine Learning-Based Portfolio Optimization follows closely at Rank 2, reflecting its strong performance in optimizing investment portfolios while maintaining reasonable costs. AI-Based Risk Management Models secure Rank 3, emphasizing their importance in financial risk mitigation and market stability. On the other hand, Algorithmic High-Frequency Trading (HFT) ranks the lowest (Rank 8), largely due to its high computational and implementation costs, despite its strong potential for profitability. Similarly, Reinforcement Learning for Trading (Rank 7) and Sentiment Analysis for Stock Prediction (Rank 6) demonstrate lower rankings, indicating challenges such as resource demands and market unpredictability.

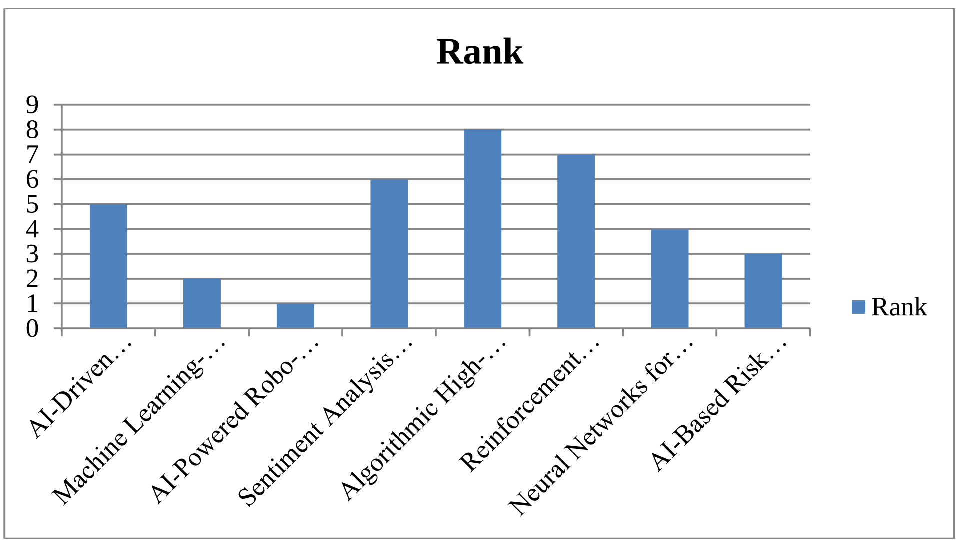

FIGURE 5. Rank

Figure 5 illustrates the ranking of AI-driven financial strategies based on the MOORA method, offering a visual representation of their relative effectiveness. The bar chart highlights the ranking order, where a lower rank indicates a more favorable performance across key evaluation criteria such as ROI, prediction accuracy, market adaptability, operational efficiency, implementation cost, and computational complexity. AI-Powered Robo-Advisors rank the highest (Rank 1), demonstrating their superior balance of cost-efficiency, adaptability, and overall effectiveness in financial decision-making. Machine Learning-Based Portfolio Optimization follows at Rank 2, confirming its strong ability to optimize investment portfolios with relatively lower costs. AI-Based Risk Management Models (Rank 3) and Neural Networks for Market Forecasting (Rank 4) also perform well, indicating their robustness in risk mitigation and market prediction. On the lower end of the ranking, Algorithmic High-Frequency Trading (HFT) ranks the lowest (Rank 8), reflecting the significant computational and implementation costs associated with this approach. Similarly, Reinforcement Learning for Trading (Rank 7) and Sentiment Analysis for Stock Prediction (Rank 6) indicate lower effectiveness due to factors like high resource demands and market unpredictability.

4. CONCLUSION

One of the most significant advantages of AI in investment strategies is its ability to leverage big data for predictive analytics. Traditional investment strategies rely heavily on historical trends and human expertise, which, while valuable, are limited in their ability to process and analyze the massive volumes of data generated in today's digital economy. AI algorithms, particularly those using deep learning and natural language processing, can analyze financial reports, news articles, social media sentiment, and other alternative data sources to provide deeper insights into market movements. This enhanced analytical capability allows investors to make data-driven decisions with a higher degree of accuracy and confidence. Machine learning models, particularly those employing supervised and reinforcement learning techniques, have revolutionized quantitative investing. These models continuously learn from past data, adapting and improving their predictions over time. Hedge funds and asset managers now deploy AI-driven quantitative models to develop sophisticated investment strategies that can identify arbitrage opportunities, optimize portfolios, and manage risk more effectively. Unlike traditional models, which may become obsolete due to changing market conditions, AI-driven models evolve dynamically, enabling them to adjust to emerging trends and potential disruptions in real time. Algorithmic trading, another area heavily influenced by AI and ML, has gained significant traction in recent years. These AI-driven trading systems rely on complex mathematical models and real-time data processing to execute thousands or even millions of trades within seconds, enhancing market liquidity and efficiency. While HFT has generated concerns regarding market stability, AI-driven trading strategies continue to shape the future of financial markets by improving execution speed and reducing transaction costs. Risk management is another crucial area where AI and machine learning have had a profound impact. AI-powered risk management systems can analyze vast datasets, detect anomalies, and identify potential risks that may not be immediately apparent through traditional methods. By leveraging AI, financial institutions can proactively monitor portfolio risks, anticipate market downturns, and implement hedging strategies to minimize losses. Additionally, AI models can assess credit risk more accurately, enabling banks and lending institutions to make more informed lending decisions. The rise of robo-advisors exemplifies how AI and ML have democratized investment opportunities for retail investors. These AI-driven financial advisory platforms leverage algorithms to provide personalized investment recommendations based on an individual's risk tolerance, financial goals, and market conditions. Robo-advisors offer a cost-effective alternative to traditional financial advisors, making professional-grade investment management accessible to a broader audience. By eliminating human biases and emotional decision-making, robo-advisors ensure a more systematic and disciplined approach to investing. The growing popularity of robo-advisory services underscores the increasing reliance on AI-driven solutions in wealth management and personal finance. Additionally, the increasing reliance on AI in investment decision-making poses systemic risks to financial markets. The widespread use of algorithmic trading and AI-powered strategies could lead to market distortions, flash crashes, and unintended consequences if multiple AI-driven systems react to market events in a similar manner. Regulators and financial institutions must implement safeguards and oversight mechanisms to mitigate these risks while ensuring the stability and integrity of financial markets. Another critical consideration is the cybersecurity risks associated with AI-driven investment strategies. As financial institutions integrate AI into their operations, they become more vulnerable to cyber threats, data breaches, and adversarial attacks on AI models. Ensuring the security and robustness of AI-driven investment systems is paramount to preventing financial fraud and maintaining investor confidence.

REFERENCES

[1]. Nair, Vikram. "AI-powered investment strategies: Enhancing portfolio management through machine learning." *Journal Of Recent Trends in Computer Science and Engineering (JRTCSE)* 12, no. 1 (2024): 1-5.

[2]. Li, Jiaqi, Xiaoyan Wang, Saleem Ahmad, Xiaobing Huang, and Yousaf Ali Khan. "Optimization of investment strategies through machine learning." *Heliyon* 9, no. 5 (2023).

[3]. Arifian, Dini, Siti Mudawanah, Herlina Herlina, and Ana Ima Sofana. "The Impact of Artificial Intelligence on

Investment Decision-Making." *Islamic Studies in the World* 1, no. 2 (2024): 93-102.

[4]. Koehler, Samuel, Niravkumar Dhameliya, Bhavik Patel, and Sunil Kumar Reddy Anumandla. "AI-Enhanced Cryptocurrency Trading Algorithm for Optimal Investment Strategies." *Asian Accounting and Auditing Advancement* 9, no. 1 (2018): 101-114.

[5]. Asere, Gbenga Femi, and Kehinde Adetayo Nuga. "Examining the potential of artificial intelligence and machine learning in predicting trends and enhancing investment decision-making." *Scientific Journal of Engineering, and Technology* 1, no. 1 (2024): 15-20.

[6]. Peter, Harry. "AI-Driven Investment Strategies: Leveraging Machine Learning for Dynamic Portfolio Rebalancing." (2024).

[7]. Prasad, Akhilesh, and Arumugam Seetharaman. "Importance of machine learning in making investment decision in stock market." *Vikalpa* 46, no. 4 (2021): 209-222.

[8]. Kumari, S. A. I. "Enhanced Portfolio Management: Leveraging Machine Learning for Optimized Investment Strategies in 2024." *J. Inform. Educ. Res* 4 (2024): 1487.

[9]. Parisi, Luca, and Marianne Lyne Manaog. "Optimal Machine Learning-and Deep Learning-driven algorithms for predicting the future value of investments: A systematic review and meta-analysis." *Engineering Applications of Artificial Intelligence* 142 (2025): 109924.

[10]. Bi, Shuochen, Wenqing Bao, Jue Xiao, Jiangshan Wang, and Tingting Deng. "Application and practice of AI technology in quantitative investment." *arXiv preprint arXiv:2404.18184* (2024).

[11]. Li, Yuming, Pin Ni, and Victor Chang. "An empirical research on the investment strategy of stock market based on deep reinforcement learning model." In *Proceedings of the 4th International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS)*, vol. 1, pp. 52-58. SciTePress, 2019.

[12]. Rane, Nitin, Saurabh Choudhary, and Jayesh Rane. "Leading-edge Artificial intelligence (AI)-powered financial forecasting for shaping the future of investment strategies." *Available at SSRN 4640828* (2023).

[13]. Wiliński, A., Aneta Bera, W. Nowicki, and P. Błaszyński. "Study on the effectiveness of the investment strategy based on a classifier with rules adapted by machine learning." *International Scholarly Research Notices* 2014, no. 1 (2014): 451849.

[14]. Gupta, Aaryan, Mayank Puri, Mayank Keshan, and Varun Tiwari. "AI in Financial Decision-Making: Revolutionizing Investment Strategies and Risk Management." In *This paper was presented at Global Forum for Financial Consumers (GFFC)*. 2024.

[15]. Brauers, Willem Karel, and Edmundas Kazimieras Zavadskas. "The MOORA method and its application to privatization in a transition economy." *Control and cybernetics* 35, no. 2 (2006): 445-469.

[16]. Karande, Prasad, and Shankar Chakraborty. "Application of multi-objective optimization on the basis of ratio analysis (MOORA) method for materials selection." *Materials & Design* 37 (2012): 317-324.

[17]. Gadakh, V. S., Vilas Baburao Shinde, and N. S. Khemnar. "Optimization of welding process parameters using MOORA method." *The International Journal of Advanced Manufacturing Technology* 69 (2013): 2031-2039.

[18]. Brauers, Willem K., and Edmundas K. Zavadskas. "Robustness of the multi-objective MOORA method with a test for the facilities sector." *Technological and economic development of economy* 15, no. 2 (2009): 352-375.

[19]. Stanujkic, Dragisa, Nedeljko Magdalinovic, Rodoljub Jovanovic, and Sanja Stojanovic. "An objective multi-criteria approach to optimization using MOORA method and interval grey numbers." *Technological and Economic Development of Economy* 18, no. 2 (2012): 331-363.

[20]. Siregar, Victor Marudut Mulia, Mega Romauly Tampubolon, Eka Pratiwi Septania Parapat, Eve Ida Malau, and Debora Silvia Hutagalung. "Decision support system for selection technique using MOORA method." In *IOP Conference Series: Materials Science and Engineering*, vol. 1088, no. 1, p. 012022. IOP Publishing, 2021.