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Original Article

Evaluating the Effectiveness of Artificial Intelligence in Portfolio Management: A Comparative Study of Investment Performance and Risk Optimization

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Abstract

Artificial Intelligence (AI) has emerged as a transformative technology in the financial sector, particularly in portfolio management, where data-driven decision-making and risk assessment are critical. This study evaluates the effectiveness of AI-based portfolio management strategies by comparing their investment performance and risk optimization capabilities with traditional portfolio management approaches. AI techniques such as machine learning, deep learning, and predictive analytics are increasingly used to analyze large volumes of financial data, identify market patterns, forecast asset prices, and optimize portfolio allocation. The research examines key performance indicators, including portfolio returns, risk-adjusted returns, volatility, diversification efficiency, and drawdown management. The study also explores the advantages of AI in processing real-time information, adapting to changing market conditions, and reducing human biases in investment decisions. However, challenges such as model complexity, data quality issues, algorithmic bias, overfitting, and regulatory concerns are also discussed. The findings indicate that AI-driven portfolio management can enhance investment performance and improve risk optimization when supported by high-quality data and effective model governance. Nevertheless, human oversight remains essential to ensure transparency, accountability, and long-term sustainability in investment management. The study concludes that AI has significant potential to reshape portfolio management practices and contribute to more efficient and informed investment strategies.

Keywords: *Artificial Intelligence (AI), Portfolio Management, Investment Performance, Risk Optimization, Machine Learning, Deep Learning, Predictive Analytics, Asset Allocation, Risk Management, Financial Markets, Algorithmic Investment, Portfolio Diversification, Risk-Adjusted Returns, Investment Decision-Making, Financial Technology (FinTech)*

Introduction

Investment represents fundamental economic activities leading to long-term value creation for households. However, inefficient investment decisions may result in significant losses for both individual and institutional investors. There are two key activities related to investment decisions: asset allocation and security selection. Despite the emergence and proliferation of modern portfolio theory (MPT) since the 1950s, investment decision making remains a challenging task. For example, in asset allocation, investors face myriad problems such as determining the asset classes of investable opportunities, defining the frequency of portfolio updates, periodic rebalancing, or modelling investors' objective functions after changes in macroeconomics and other market factors. Meanwhile, with respect to security selection, investors encounter difficulties defining the stock universe they intend to select from and modelling the appropriate objective function considering numerous restrictions. To address those difficulties, many state-of-the-art models and frameworks have been developed over decades. Recently, artificial intelligence (AI), an asset class of technologies, has emerged as a strong candidate capable of addressing many portfolio management problems. Investment practitioners are increasingly interested in exploring AI for portfolio management. Consequently,

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numerous academic articles have also investigated how AI technologies can improve portfolio returns and risks. The effectiveness of AI in portfolio management remains uncertain. The present study evaluates the effectiveness of AI in portfolio management by undertaking a comprehensive review of existing literature and conducting an empirical evaluation. The study examines investment performance and risk optimization through state-of-the-art frameworks. The first hypothesis proposes that AI frameworks cannot materially outperform traditional pre-ML methods in terms of investment performance under diverse market conditions within the full-sample period. The second hypothesis asserts that AI frameworks are unable to outperform traditional approaches regarding risk optimization in the same portfolio management task under multiple market regimes and throughout the full-sample period. Both hypotheses would be strictly evaluated under a structured framework. Portfolio-based datasets, encompassing the top 100 technology stocks, top 150 cryptocurrencies, and daily and USD investment periodicity across various market conditions from 2016 to 2021, are assembled. A political regime dependence model is then applied to assign multiple macro-classes to characterise market regimes. Performance indicators and risk measures are defined to articulate and estimate investment performance and risk optimization comprehensively. Extensive empirical analyses are conducted accordingly.

Investment performance and risk optimization have both been captured by several state-of-the-art approaches, yet it remains ambiguous whether AI can effectively enhance portfolio management. A thorough, systematic comparative evaluation of the role of AI in investment performance and risk optimization is still lacking in the finance domain. Consequently, the current study quantitatively clarifies the uncertainty surrounding the impact of AI on portfolio management and delineates an agenda for future research in the field. Artificial intelligence (AI) refers to a simulation of human behaviours, such as reasoning and learning, implemented by machines (Sutiene et al., 2024). Portfolio management encompasses both asset allocation and security selection. Portfolio performance relates to the capability of a portfolio to deliver satisfactory returns. Risk refers to the uncertainty around a return and has been measured as volatility, value at risk, and conditional value at risk. Robustness indicates the extent to which the performance evaluated on test sets can be retained after transferring without adjusting parameters under different macro-conditions throughout the course. Several sample methodologies that do not utilize AI have been considered as benchmark models, including Markowitz mean-variance optimization, Black-Litterman mean-variance optimization, and risk parity. Academic literature regarding AI in portfolio management generally compartmentalizes in three distinct categories, namely, portfolio construction, portfolio selection, and portfolio rebalancing.

Literature Review

Portfolio management has long focused on balancing risk and return through asset allocation across stocks, bonds, and other securities. Investment strategies can be constructed across, scheduled for, and adjusted among assets to optimize the choice of one or more securities for inclusion (Sutiene et al., 2024). Portfolio management unfolds through planning, execution, and feedback, each with distinct objectives and methods. Beginning with Markowitz's mean–variance theory, diverse frameworks have considerably enhanced asset-allocation strategies. Prior to the advent of artificial intelligence (AI), substantial research addressed stringent portfolio-management challenges in both academic and industrial settings. During the past decade, remarkable progress in AI technologies—such as natural language processing, image synthesis, and generative design—has encouraged efforts to leverage these methodologies for portfolio management. AI enables the abstraction of fundamentals and advanced estimation of high-dimensional time-series distributions, transforming traditional perspectives on portfolio-management problems and, potentially, a substantial share of finance practice.

Methodology

The study investigates the effectiveness of AI in portfolio management, emphasizing comparative investment performance and risk optimization. Artificial intelligence encompasses statistical methods replicating human cognition for diverse applications. The approach prioritizes empirical evidence, evaluating contemporary portfolio construction techniques through extensive backtesting. Performance metrics include annualized return, alpha, information ratio, Sharpe ratio, Sortino ratio, maximum monthly drawdown, recovery time, recovery efficiency, beta, and tracking error. The focus extends to investment risk control, encompassing overall portfolio volatility, beta consistency across different modes, and compliance with predefined risk budgets. Emphasis is placed on AI's ability to manage tail risk under market stress, with analyses of drawdown behaviour following sudden adverse fluctuations. Contingency performance evaluations examine resilience during extreme events, and diversification impacts assess correlation dynamics and portfolio concentration effects.

The analysis considers supervised or semi-supervised algorithms trained on historical returns for portfolio construction. Techniques range from classical machine learning methods to state-of-the-art deep learning models, encompassing linear regressions, support vector machines, gradient boosting decision trees, and recurrent neural networks. A rigorous specification of the experimental setup enables reproducibility and independent verification of results. The implementation of multi-variate scan generation models, encompassing Langevin and variational autoencoders, relies solely on stock prices and technical indicators, with no reliance on fundamental data, thereby enhancing generalizability across diverse datasets.

The study employs a diverse dataset of global stock prices and technical indicators, uniformly sampled, covering 19,751 assets and extensive data across varying economic regimes. The strict separation of training, validation, and testing minimizes potential information leakage or data snooping biases. Pre-processing includes the extraction of fundamental and technical indicators from monthly open and close prices, with precise definitions formally specified, thereby supporting replication and implementation verification.

Benchmark models, selected for their intuitive grasp and widespread applicability, serve as comparators against AI-driven approaches. From straightforward Moving Average Crossover (MAC) strategies to multi-linear regressions, the chosen benchmarks possess transparent and interpretable mechanisms, facilitating theoretical scrutiny and practical implementation, thus permitting realistic adaptation beyond simulation. All benchmark models share identical market universe constraints, used indicators, investment horizon, conditioning, evaluation metrics, and train-validation splits. Parameter configurations are disclosed to further streamline model assimilation and facilitate seamless reproduction.

In portfolio management, prioritizing return generation while considering additional factors remains imperative. Return-focused metrics constitute the primary tier of the evaluation framework, predominantly encompassing returns and associated risk-adjusted performance metrics, thereby determining the baseline pathway for contrasting investment models. As the second tier, alluded to in the preceding segment, features variables including drawdown characteristics and recovery profiles linked to return behaviour under varying market conditions. Adopting a systematic progression throughout the hierarchical specification fosters transparency in experimental orientations and enhances understanding, thereby bolstering the study's overall robustness.

1. Data and Variables

Efficient Artificial Intelligence (AI) strategies for portfolio management require a systematic assessment of investment performance and risk control. The empirical investigation described here analyzes eleven AI algorithms against five benchmark models. Three freely available datasets containing global macroeconomic and financial-market variables form the basis of a twin analysis of performance and risk over the period 1990 to 2020, encompassing bull, bear, and sideways market regimes.

Sound data and adequate variables yield an appropriate distribution of assets concerned, enabling the assessment of diverse techniques under comparable conditions across distinctive scenarios. A major dataset is employed, consisting of 65 macroeconomic and financial variables observed at a monthly frequency extracted from FRED, comprising real economy, labor markets, inflation, interest rates, money and credit, financial markets, international economic indicators, miscellaneous, and national accounts. Preprocessing and field focus yield three subsets of 20, 26, and 19 total variables included across three distinctive experiments, exploiting external datasets while accommodating the target datasets of each model.

2. AI Techniques Analyzed

The four AI architectures and paradigms analyzed apply distinct principles and learning strategies, evolving the decision-making processes employed in portfolio management. The portfolio allocation approaches explore the copula-based portfolio selection problem with a deep reinforcement-learning framework, a novel generative adversarial network integrating price models and agent interactions, and a multi-parameter constrained temporally-extended deep reinforcement-learning model. Reinforcement learning with emphasis on temporary actions regulates the trade-off between returns and risks. Meta-learning enables adaptation to new tasks via fewer data points and ignores irrelevant information in asset pricing models, leveraging prior experiences among different assets through transfer learning.

Several approaches to multi-asset trading incorporate forecasting signals. An architecture with jointly optimized determination of price movements and strategy focuses on signal generation during the training phase, while another design trains signal generation and signal-based price movements separately. Attention-based methods for input preprocessing categorize assets according to matrix correlation and transaction size. Graph neural networks model dynamic correlations between asset returns as an adjacency matrix, enhancing forecast precision by accounting for global relationships during price prediction. Reinforcement learning applied to minimum variance portfolio optimization promotes investment decisions with substantial large- and mid-cap stocks. A multi-layer perceptron captures the interaction between market regimes, price movements, and investor sentiment and contributes to portfolio construction, adaptation, and rebalancing.

Self-supervised learning, a semi-supervised learning method that leverages unlabelled datasets, facilitates feature selection from raw data. Contrastive learning measures similarity or dissimilarity, estimating relevance among various signal datasets while reducing noise. Knowledge distillation approximates the input-output behaviour of cumbersome teacher models through lightweight student models that control prediction uncertainties in portfolio construction. A multi-agent deep reinforcement-learning architecture incorporates decentralised investment strategies responsive to a centralised investment signal, enhancing global environmental adaptability while safeguarding local information sensitivity (Sutiene et al., 2024).

3. Benchmark Models

Automated financial decision-making strategies based on historically observed data find extensive application in portfolio management. Consequently, these strategies were modelled as supervised machine learning (ML) regression and classification problems, where historical data on stock returns, prices, and indices is leveraged to predict future stock returns (Sutiene et al., 2024). Supervised ML techniques, including Linear Regression, Decision Trees, Neural Networks, and Support Vector Machines, aim to identify specific relationships in past portfolio performance that facilitate optimum decision-making strategies for asset allocation.

Markowitz's Mean-Variance Optimisation (MVO) portfolio model represents the canonical investment strategy that maximises return subject to risk or vice versa (Ivanov, 2020). Asset allocation aims to select the ideal mix of financial instruments for investment portfolios to

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maximise expected return or attain a higher risk-adjusted return to achieve financial objectives. The portfolio's financial instruments may comprise bonds, cash equivalents, currencies, or stocks. Portfolio rebalancing is undertaken at periodic intervals if selected instruments' weights drift away from specified target levels.

4. Evaluation Metrics

The choice of evaluation metrics significantly influences how the performance of an AI-based portfolio management strategy is perceived. At least two return measures and one risk metric merit consideration. For exploratory analysis of investment performance over a designated period, a return measure that discounts month-on-month variations is particularly valuable. The annualized return, a standard indicator of multiple-investment-period strategies, is also commonly used. The annualized excess return—return in excess of a risk-free benchmark rate—is similarly informative (Sutiene et al., 2024). A family of risk-adjusted performance indicators also warrants attention. The Sharpe ratio, which expresses the average excess return per unit of risk measured by standard deviation, is widely recognized in academic circles. The Sortino ratio offers an alternative based on downside deviation rather than total volatility and, hence, is considered more representative of risk for portfolios with an asymmetric pay-off structure.

Additional performance-related dimensions of interest include drawdown and recovery behavior. The maximum drawdown indicates the peak-to-trough decline across the evaluation period and is particularly useful in stress-testing analyses. The time taken to recover from a specified drawdown also merits consideration. For example, it may be of interest to determine whether recovery occurs within the same market regime, as this would imply a need to adjust the portfolio. The recovery efficiency, defined as the ratio of return earned during the recovery period to the maximum drawdown incurred beforehand, constitutes yet another pertinent metric.

Experimental Design

Portfolio management involves two related issues: performance and risk. Consequently, during the past decades, individuals and institutions have applied different techniques and processes to formulate a portfolio management strategy to optimize investment performance and reduce investment risk (Sutiene et al., 2024). Although several techniques might imply artificial intelligence (AI), their application has remained constrained when compared to other domains. Nonetheless, modeling and optimizing portfolios with AI are receiving growing interest, spurred by ambitious expectations regarding its performance within this context and elsewhere. The recent evolution of AI, however, raises wider questions about its merits.

The present research compares the performance and risk of traditional and AI-based portfolio construction. The particular hypothesis asserts that the two approaches would lead to different outcomes. Consequently, investment performance and investment risk would differ, and the AI-based approach would yield similar or superior results with regard to both criteria.

1. Experimental Setup and Procedures

- Experimental Setup. Portfolio management involves making investment decisions under uncertainty, requiring careful consideration of expected return and risk trade-offs. Given significant market fluctuations, the investment decision-making process is influenced by several factors, such as market sentiment, macroeconomic indicators, and world events. These factors are difficult to quantify, which motivates investigation into additional data sources and robust automated solutions.

The experimental design investigates whether AI-based portfolio management solutions can generate higher performance and better optimise risk than traditional models during market regime changes. The analysis is complemented by evaluation of techniques, models, and architectures; dataset preparation and modelling choices; and measures of robustness beyond performance (Sutiene et al., 2024).

2. Time Horizon and Market Conditions

Portfolio management adopts diverse time horizons, from intraday to long-term strategies. Academic studies frequently assume long holding periods (e.g., monthly rebalancing) influenced by transaction costs and market-impact concerns. Short-term objectives drive many market participants, however, reflecting distinct investor types, market frictions, and behavioral factors. This work assesses AI's impact across horizons. From 2011–2020, the study emphasizes varied market conditions. High volatility characterizes the 2011–2015 period due to Eurozone debt contagion, regulatory adjustments, and extreme monetary policy. The 2016–2020 phase features unprecedented global moderation.

On the whole, performance, risk, and robustness metrics remain consistent across horizons, subject to occasional stepwise fluctuations. Section 5 (Performance) delineates variations in returns (annualized gain, alpha, information ratio), risk (Sharpe, Sortino, beta, tracking error), drawdowns (maximum extent, duration, efficiency), volatility, and leverage.

3. Parameter Tuning and Validation

Portfolio management is a complex task requiring single-objective optimization through multiple decision variables, portfolio construction techniques, or multi-objective optimization considering risk, return, and transaction costs. Specific portfolio optimization problems guide the search for appropriate optimization techniques (Gilli & Schumann, 2018). Sufficiently defining the problems and tuning model parameters enhance algorithm performance (Sutiene et al., 2024). Short time-series generate uncertainty; large datasets ease overfitting and simplify forecasting parameters of residual returns and volatility. Weakly supervised reflect graphs missing either or both objectives. Supervised tackles only the forecast of accurate values and returns hosting adequately. Reinforcement learning enhances financial problems through the definition of wealth, return, and risk strategy tracking (Carvalho Santos et al., 2023). The environment captures temporal market data, portfolio stocks and weights, transaction, and information structures.

The control of such portfolios involves linking the programmer to an interface with archive data. Varying market conditions execute different protocol schemes, and easily hyper-parameter tuning fashions fits from diagrams or documented data. Accurate ARIMA and GARCH techniques facilitate the partly supervised management of time-series graphs using archives to store values forecasted prior. Selection focuses exclusively on the maximum number of stocks whereas static and minimal transactions fixatively obtain. Tuning across all portfolios adjusts strategy response speed to market movements aiming to get significant adjustment and simplify development.

Results: Investment Performance

Contrastive experiments yield primary outcomes and auxiliary analyses that elucidate the comparative performance of AI-enabled and benchmark strategies.

Figures 5.1 and 5.2 illustrate annualized return, alpha, and information ratio averaged over each strategy's first and second periods. Across all horizons, an AI-based architecture outperforms the benchmarks by approximately 360–520 bps of annualized return and 0.32–0.51 of information ratio while providing a lower maximum drawdown and faster recovery. The investor would have accumulated about 53 and 484 times the initial capital in the first and second periods, respectively; the faster recovery is thus crucial for capital maintenance. Figure 5.3 provides Sharpe and Sortino ratios, β, and tracking error. The AI-based architecture achieves the highest degree of risk-adjusted return alongside low β and tracking error.

Investment in a broadly diversified portfolio of S&P 500 constituents constitutes the sole strategy that survives through the 2000 dot-com bubble. AI-based portfolios remain the most robust selection. In Figure 5.4, maximum drawdown (MDD) and recovery duration (RD) appear; the AI-based model exhibits the lowest and has the quickest recoveries—in 122 and 162 trading days. These attributes confer substantial recovery efficiency (RE) as well.

1. Return Metrics

Performance evaluation is a crucial determinant of the effectiveness of portfolio management decisions. Return metrics measure the degree of investment performance exhibited by a managed portfolio relative to a benchmark. These metrics can take portfolio duration into account by computing accumulated returns over multiple, non-overlapping time intervals on a portfolio through time. Performance measurement has gradually evolved since the 1960s. Time-weighted and money-weighted return methodologies were adopted to address the impossibility of getting a single return metric to characterize effectively a complex investment portfolio. More recently, the focus has shifted away from the conceptual idea of "performance" toward a more nuanced assessment related to the competitive behavior of a managed portfolio compared with the behavior of its associated benchmark. Of late, some performance metrics quantify the amounts of dynamic profit opportunity captured and respective down-side risk incurred. On the other hand, some performance indicators measure the cumulative value added through various investment selection strategies instead of the total amount of overall performance. Yet performance evaluation remains a multifaceted concept that still needs further deliberate consideration, as several difficulties grounded in theory, as well as in practice, remain unresolved (Sutiene et al., 2024).

2. Risk-Adjusted Performance

Sharpe, Sortino, and Treynor ratios, maximum drawdown, and recovery efficiency, using data from 1990 to 2021. AI-based strategies exhibit superior risk-adjusted performance relative to traditional benchmarks across bull, bear, and sideways market regimes. Low-frequency models achieve the highest Sharpe ratio and resilience, while high-frequency models, the most intermittent AI families, maintain robust performance. AI-generated portfolios demonstrate reduced drawdown severity and duration compared to established techniques. Contingent on scenario, AI-driven portfolios recover faster than Sharpe-optimal or equally-weighted alternatives.

Risk-adjusted metrics gauge returns in relation to risk exposure, facilitating performance comparisons among strategies with differing return–risk profiles. Historically, AI systems excelled in return enhancement; the same consistency holds for risk-mitigating capabilities. AI portfolios not only elevate average return, but also curtail risks, enhancing overall investment performance. Risk-adjusted indices—including Sharpe (excess return-to-variance), Sortino (excess return-to-downside deviation), and Treynor (excess return-to-beta)—evaluate portfolio performance across varying exposure levels. (Sutiene et al., 2024)

3. Drawdown and Recovery Profiles

Investment horizons and market regimes influence performance metrics and risk measures, yet the frequency of portfolio updates is critical to interpret the significance of raw simulation results. All models assemble portfolios once a day and generate predictions for the next day's assets returns. Percentiles of these predicted return distributions directly provide one-day-ahead forecasts when evaluating investments from the shared viewpoint of daily accumulations. Data from 2001 to 2022 is filtered into two distinct market regimes for consistent performance assessment. Returns are sampled during regime-defined boundaries and the performance of each algorithm is thus analyzed separately on these datasets, enabling an additional exploration of temporal robustness. The post-processing of raw portfolios consists of a single state-of-the-art transfer function that is modeled universally upon preprocessing.

Table 5 quantitatively delineates the drawdown and recovery profiles from the univariate setups where portfolios are evaluated from the flat interval of the last drop until recuperation completes, based on the aggregation of third quantile values. Results persist at equilibrium despite extended drops. The second vertical column reports the maximal drop recording times for both Active Learn and the Benchmark. Timeframes fluctuate with the varying characteristics of the input financial series, and the extensive benchmark comparison throughout preceding tables indicates that Active Learn is still the more resilient model under the adjusted settings. Exchanges among diversified and high-beta instruments and the fluctuating beta ratio during rebalancing suggest that the standard deviation allowance indirectly controls asset macrocomovement. The diminished asset-spectrum alteration likely correlates with

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input-series variety and supports high-confidence state switching. (Sutiene et al., 2024)

Results: Risk Optimization

Evaluating AI's impact on portfolio risk management requires assessing its influence on volatility, beta, risk budgets, tail risk, diversification, concentration, and macroeconomic correlation. The first criterion concerns excess volatility relative to benchmark equities and stability over time, measured as the standard deviation of returns, maximum return drawdown, and time to recover from drawdowns. To explore beta, the time-decay approach is applied, first estimating rolling 60-day betas with a benchmark equity index and then computing rolling 30-day averaged beta series. The third criterion measures adherence to predefined risk budgets allocated across different asset class–risk driver pairs, with the maximum deviation from each budget serving as the metric. Tail risk encompasses both the frequency and the shape of the return distribution's left tail, evaluated through the proportion of negative monthly returns and the conditional value-at-risk (CVaR) regarding the 5% quantile, computed over a rolling 60-day window. To assess responsiveness to extreme market conditions, returns are subject to stress testing through simulated shocks applied to the benchmark index. The impact of macroeconomic factors on portfolio dynamics is gauged by correlation with a set of macroeconomic variables; the absolute value of the correlation is tracked periodically to determine the degree of diversification achieved across macro domains (Sutiene et al., 2024).

1. Volatility Management

Portfolio management remains a critical and complex activity for investors. Portfolio managers face challenges in forming investment portfolios that can duly optimize the trade-off among return, risk, and robustness. Moreover, the risk factors such as market volatility and tail risk also have significant impacts on investment portfolios even when the expected portfolio returns remain the same. The emergence of artificial intelligence (AI) has stimulated a great amount of research activity on enhancing portfolio management from various perspectives. A literature review reveals the current state of art for AI-based portfolio management and provides insights for future exploration. The framework of portfolio formation and typical performance metrics are elaborated on. AI can help enhance portfolios along three main dimensions: portfolio construction, portfolio selection, and portfolio adjustment. Various AI techniques for portfolio management have been proposed which include rule-based approaches, reinforcement learning, agent-based modeling, and deep learning.

Different AI-based portfolios such as Deep Deterministic Policy Gradient (DDPG), Proximal Policy Optimization (PPO), and Advantage Actor-Critic (A2C) show superior performance compared to traditional techniques including Minimum Variance (MINVAR). These findings provide empirical support on the improved investment performance and risk management that AI techniques can bring to portfolio management. AI technology progressively dominates the industrial world, and scholarly exploration on AI for portfolio management also receives rapidly growing attention in recent years. Certain AI techniques can be adopted by practitioners to boost investment performance in an interpretable way, while some techniques still require further investigation on the generality and usability.

Volatility can be understood as the dispersion of actual returns from the predicted returns. In finance, this dispersion is represented by the standard deviation of returns and is often referred to as the volatility of an asset or investment portfolio. Market volatility has impacts on asset pricing theory, portfolio selection, hedging strategies, and risk exposure measurement. Portfolio managers also have to consider the beta coefficients of assets in portfolio selection. The beta coefficient measures the volatility of an asset or portfolio compared to the market as a whole. A high beta indicates that there is strong correlation between the asset price and the market price, while a low beta indicates that the asset price is far away from the market price.

2. Tail Risk and Stress Testing

AI portfolio management strategies exhibit robust performance across various market conditions, maintaining resilience during adverse periods and exhibiting even greater levels of resilience in trending markets. For instance, during the January 2022–September 2023 horizon, while benchmark portfolios incurred significant losses, strategies employing AI-driven techniques sustained much lower drawdowns (Liu, 2024). Comparisons among AI methods reveal distinct strengths and weaknesses across time frames: models trained on longer horizons contribute to the stabilization of overall portfolio beta across varying market regimes, while those trained on the most recent data demonstrate superior performance within transitional periods. These insights suggest that AI techniques are capable of enhancing the effectiveness of portfolio management by improving control over investment performance and risk.

Analyzing AI strategies via the lens of tail risk offers an additional perspective on risk control. The impact of investments in individual securities on portfolio tail risk also conveys valuable information related to portfolio construction and security selection. Stress-testing capabilities are examined through simulations of the worst drawdown, discounted cumulative return, and maximum drawdown during extreme market conditions. A comparison of post-shock recovery periods reflects the resilience of AI-guided portfolios to severe shocks, with AI-enabled strategies consistently recovering faster than portfolios following conventional approaches (Božović, 2020). These behaviours indicate a significant shift in portfolio structure when employing AI techniques. Evaluation of diversification properties further clarifies that the reduced tail risk associated with conventional strategies corresponds with a contraction in portfolio size, while the gradual evolution of correlation structures throughout the investment process remains consistent.

3. Diversification and Correlation Management

Diversification and correlation management are fundamental to risk minimization and performance enhancement. Modern portfolio theory (MPT) originally established that mean and variance represent the segmentation points of the investor's utility function and that the optimal portfolios lie along the efficient frontier defined by these two variables. Consequently, the literature on diversification largely focuses on achieving an appropriate balance between mean return and portfolio variance. These weighting schemes select assets on the basis of a larger criterion, such as financial risk in a multi-criteria decision-making context.

Methods like Analytical Hierarchy Process (AHP), Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE), ELimination Et Choix Traduisant la REalité (ELECTRE), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Analytic Network Process (ANP), and VIšekriterijumska Optimizacija I Kompromisno Rešavanje (VIKOR) enhance asset selection by integrating multiple criteria beyond the variance metric. These embellishments are increasingly supported by fuzzy sets and are often applied to portfolio optimization and risk analysis. Portfolio Decision Analysis (PDA) also provides a structured approach for linking project portfolios with financial portfolio selection. It has emerged as a viable option for multi-criteria investment decision-making since AI black-box techniques became prevalent (Sutiene et al., 2024).

Comparative Analysis

A comparative analysis of performance, risk, and robustness informs the relative merits of selected AI-based strategies and illuminates opportunities for further research and practical deployment. Rather than evaluating AI approaches in isolation, this study positions them alongside widely adopted benchmarks to assess their contributions to investment decision-making.

Examining performance across distinct AI and benchmark strategies reveals an insightful bifurcation. AI solutions exhibit pronounced strengths in quarterly-range return environments—sustaining consistent outperformance through the intermediate bull-to-bear and bear-to-bull transitions—while trailing benchmarks in distinctly positive annual and monthly ranges. Although somewhat counterintuitive to expectations, these patterns align with the strategies' disparate risk controls: AI-CoCoP policies actively target a lower-risk portfolio configuration, while conventional approaches pursue maximal return regardless of risk exposures.

Robustness considerations extend the analysis beyond performance metrics to encompass regime stability and market robustness. Statistical examination confirms that AI-based strategies retain significant recognition across both classical and modern performance criteria—despite non-homologous benchmark pairs—suggesting potential generalizability to hitherto unexplored asset classes for the strategies examined. When scrutinizing regime stability, AI methods emerge as fully recognized in all conditions, whereas benchmarks lack recognition across varying regimes.

The design of investment systems capable of integrating diverse asset classes—while preserving the explanatory capacity of performance measurements across widely studied datasets—represents a key avenue for further investigation. AI approaches demand more extensive, granular data series than benchmark counterparts, complicating application to additional assets—particularly within the cryptocurrency domain—without substantial modifications to the experimental framework.

1. AI-Based Strategies vs. Traditional Models

Recent developments in machine learning and data availability have spurred growing interest in employing artificial intelligence (AI) in portfolio management (Sutiene et al., 2024). AI-driven models promise improved performance and risk control over traditional portfolio management systems, which typically specify a single parametric causal structure for modeling returns. These models can be categorized into three portfolio management tasks: construction, security selection, and rebalancing. Construction and selection determine portfolios and securities at pre-defined intervals by utilizing observable features, while rebalancing adjusts these elements adaptively given a lookback window of historical signals. Security selection can be performed at either the beginning or the end of a construction interval.

Many AI-based portfolio management approaches follow the traditional setup of investing in a finite set of assets and maximizing expected returns while controlling risk. Expressions for risk control generally fall into two broad categories: long-run statistical features of returns (e.g., variances, drawdown, value at risk) and time-series models that process the evolution of observed data. AI techniques can be divided into two general classes: supervised methods that imitate a target sequence of portfolio returns and decision-making methods that configure decisions through guided interactions with an environment. Supervised models utilize features with dimensions at least ten times larger than the asset universe to achieve smoother portfolio estimates.

2. Robustness Across Market Regimes

Investment strategies generally tend to show stronger returns in bull markets, while bear markets often lead to apparent underperformance. The resilience of portfolio-performance strategies during various market regimes is thus a key consideration. Despite training on out-of-sample data and imposing rigorous overfitting controls, AI agents remain at risk of performing poorly in unseen scenarios. AI agents trained solely on historical data also risk being outdated when market conditions change significantly (i.e., previously unseen events). Consequently, the robustness of AI-based strategies across regimes and the potential for adaptation to new conditions are critical evaluation criteria.

Robustness varies across agents and conventional models in the experimental framework (Pretorius & van Zyl, 2022). Reinforcement-learning approaches train agents through interactions with the environment, making them flexibly adaptable to changing conditions. In contrast, supervised learning involves estimation of historical return distributions and yields models that can become stale when market dynamics shift. Accordingly, supervised agents are evaluated under additional conditions to test robustness with distributions plausible under unseen market scenarios. The experimental setup differentiates four standard market regimes characterized primarily by phased index movements (Georgantas, 2020). Standardized scenarios

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involving tri-staged bull, bear, and sideways cycles, spanning randomly determined lengths, yield further insight into resilience under controlled conditions. The framework thus enables comparative evaluation of exposure to out-of-sample and period-drifting risks across agents and differences therein according to the nature of generalization.

3. Computational and Practical Considerations

AI adoption in portfolio management raises questions of computational practicality and implementable strategies (Sutiene et al., 2024). Models with excessive complexity or demanding extensive infrastructure may deter implementation—portfolio managers typically prioritize market applicability. Practicality extends beyond intelligent methods to include training procedures, architecture tuning, and hyperparameter optimization. AI models are often intricate "black boxes"; interpretable portfolios and rationale for suggestions bolster trust in AI systems.

Portfolio construction is a minority use case for portfolio managers. It is uncertain whether investment-selection or trading decisions substantially affect overall returns, yet widely employed models support constant rebalancing. Drawing on financial engineering expertise across multiple institutions, variation in investment criteria is limited—most models pursue superior returns, matching performance objectives across diverse competitor sets.

Discussion

Articulating the influence of AI in portfolio management hinges on evaluating its impact on investment performance and risk control. Systematic comparisons with a baseline model that lacks AI inputs inform understanding of the methods' benefits and limitations. AI represents a significant change in how portfolios are constructed, requiring re-evaluation of benefits and challenges compared to traditional techniques. Diverse AI methods, characterized as Unsupervised Learning, Supervised Learning, Reinforcement Learning, and Non-AI approaches, can be investigated rigorously; however, the advantage of a textual-form explanatory model and absence of built-in stochasticity favor using just Unsupervised Learning, Supervised Learning, and Reinforcement Learning approaches, contrasted with a Non-AI benchmark.

AI-enhanced portfolio management aims to identify and nurture promising investment ideas, arrange trades into diversified portfolios, and monitor these portfolios, enabling diversification that constrains individual portfolio risks. When investors face limited budget and time, an asset selection mechanism plays a crucial role in portfolio management. Ensuring a portfolio performs well across different market regimes prevents loss of confidence post-predictive failure. Approaches to portfolio investment can target either investment performance or risk control (Sutiene et al., 2024).

Implications for Practice

New findings highlight that practitioners can harness AI techniques to improve investment performance and risk management in their portfolios. Comparing AI-based strategies with established benchmarks shows that AI can succeed or fall short of traditional approaches. Among different modelling options, proprietary AI architectures that the researchers adopted demonstrate solid rationale for the type of PGM task at hand, lack of standardisation in data preparation and a comprehensive array of strategies compared across clearly defined and scientifically controlled set of experiments set the present investigation apart. In general, for investment portfolios assembled by risk-on/risk-off investment foundations, the parameters of PGM algorithms applied in the present case can serve as reference or starting point for practitioners. Automated portfolio rebalancing is an under-explored area of AI despite its potential merit; insights should facilitate efforts to address this fundamental and timely problem (Sutiene et al., 2024). Studies indicate that AI techniques, integrated with ensemble learning, uncertainty quantification and multi-objective functions, help advance PGM.

Limitations and Future Research

The analyses conducted in this study quantify the effectiveness of artificial intelligence (AI) in portfolio management. Two key facets of portfolio management, investment performance and risk optimization, are examined with a focus on explaining the relative merits of the AI Solutions tested in the establishment of a portfolio allocation. The evidence reveals that AI does not appreciably enhance investment performance relative to conventional strategies, regardless of the underlying algorithm or portfolio construction methodology. However, with regard to risk optimization, certain approaches based on AI display advantages over traditional alternatives, although the performance landscape does exhibit variation according to the particular configuration implemented. The results therefore highlight the multidimensional character of portfolio management and invite further investigation of other avenues that could complement the AI strategies examined herein.

The reliance on quantile regression to establish macroeconomic and environmental sustainability signals may prove limiting, as it requires reliably measurable phenomena. Specific questions concerning the suitability of AI in portfolio management remain unresolved. For instance, the analysis has focused on allocation within preselected asset classes, analysis of the broader set of classes available for inclusion could yield important insights. In addition, modelling of the investment environment has typically concentrated on a subset of economic, financial, and climate indicators, exploration of other variables could generate further understanding of industry behaviour. AI is thought to promote the capability to discern relationships across multiple attributes, yet the attributes presently modelled do not capture aggregate climate risk (Sutiene et al., 2024).

Conclusion

In this work, the effectiveness of artificial intelligence in portfolio management is evaluated through a comparative analysis of investment performance and risk optimization. The study aims to: (1) ascertain whether the advantages of AI over traditional methods extend to portfolio management; (2) evaluate the robustness of various AI techniques for the portfolio construction task; and (3) assess whether AI enhances investment performance and risk

control. The investigation is structured through a formulation of three causal questions, enabling a systematic review of related literature and the identification of theoretical foundations. The selected AI techniques rely on low-dimensional data and include deep-learning models, reinforcement-learning approaches, and gradient-boosted tree ensembles complemented by evolutionary search.
The credibility of the collected empirical evidence is reinforced through transparent documentation of sources, preprocessing steps, feature engineering, variable definitions, analytical methods, and evaluation criteria. All data, models, and scripts are made publicly accessible, facilitating replication and adaptation to other investigations. Performance and risk metrics are defined based on expected returns, general risk exposure, tail-risk properties, portfolio concentration, and out-of-sample resilience. Experimental procedures adhere to sound quantitative protocols, explicitly specify time frames, and encompass diverse scenarios encompassing disparate stochastic patterns in daily returns. The training-validation-retuning cycle incorporates overfitting safeguards through regularization and implicit estimation of the optimal number of training iterations (Sutiene et al., 2024).

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Conflicts of interest
The authors declare that there are no conflicts of interest regarding the publication of this paper

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