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Evaluating Modern Quantitative Methods for Investment Portfolio Management under Market Uncertainty

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Abstract:

This study evaluates the effectiveness of advanced quantitative techniques, Monte Carlo simulations, AI-driven models, and Genetic Algorithms in enhancing investment portfolio management beyond Traditional Modern Portfolio Theory limitations. Analysing financial data from 2014-2024, this study assessed performance using Sharpe Ratio, Value-at-Risk, and

Conditional Value-at-Risk across various market scenarios including black swan events. Findings demonstrate that Genetic Algorithms achieved the highest risk-adjusted returns while minimizing volatility, AI-driven models provided superior adaptability to market fluctuations, and Monte Carlo simulations significantly improved risk assessment compared to traditional approaches. The integration of green bonds into AI-optimised portfolios successfully balanced financial performance with sustainability objectives, appealing to environmentally conscious investors. This research confirms that AI and Genetic Algorithm approaches consistently outperform traditional models in optimising risk-adjusted returns under volatile conditions. Portfolio managers should consider implementing hybrid quantitative approaches that combine AI-based decision-making with Monte Carlo stress testing to enhance investment resilience and strategic planning in dynamic financial environments.

Keywords: portfolio optimization; risk management; financial analytics; market volatility; quantitative modelling; green bonds.

JEL Classification: C63, G11, G32, C61, Q56, G17.

Introduction

Investment portfolio management is important in maximizing returns while minimizing risks, particularly in an environment characterized by market uncertainty (Cheng et al., 2023). Geopolitical events, economic cycles, and sudden financial problems complicate financial markets (Korsah et al., 2024). This means there is a need for new ways to evaluate risk and make decisions. Traditional portfolio management techniques are essential, but they do not always work with the volatile nature of today's financial systems (Byrum, 2022). The financial markets are volatile because of fast technological progress, algorithmic trading, and global business possibilities. Markowitz's Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM) have been used to help diversify and adjust risk-adjusted results for many years (Jones & Trevillion, 2022). These old models assume that gains are spread out evenly and markets work well, but that is not always true. When things are unclear, investors need new ideas that can help them quickly adapt to changes in the market and keep their portfolios stable. Green investors looking to allocate their assets sustainably need sophisticated risk management strategies to keep up with the ever-changing financial markets. Green investors prioritize portfolios that balance profitability with environmental effect, and the interest in green bonds has increased as a result of the financial markets' shift towards sustainability. Green investors want new ways of investing that cater to their changing tastes while also meeting their environmental goals and financial returns targets.

A good answer would be to use quantitative financial modelling, which makes evaluating risk and optimizing portfolios easier. Tools like machine learning, stochastic optimization, and Monte Carlo models can help buyers make efficient choices. These tools make scenario-based analysis, risk forecasting, and adaptive portfolio rebalancing possible. This gives investors more ways to deal with the unknown. AI and machine learning look through vast amounts of financial data for patterns and links to make better business plans. This makes figuring out and making choices about asset allocation easier. This study looks at how quantitative modelling can help people handle their stock investments and bonds when the market is unstable. The study's main objectives are to answer this question: (1) assessing Monte Carlo simulations' risk estimation, (2) machine learning models' portfolio allocation, (3) genetic algorithms and Bayesian optimization, and (4) portfolio performance using standard risk-return measures. This paper examines these issues to demonstrate how quantitative tools aid stock management in difficult financial conditions.

The literature on the topic is reviewed in Section 2, focusing on old and new ways of managing portfolios. Section 3 explains the research methodology, including the data sources, modelling methods, and metrics for measuring success. Section 4 shows the outcomes of using financial models to improve a portfolio. Section 5 explains the results in terms of theoretical frameworks and real-world consequences. Finally, Section 6 summarizes the study by listing the most critical findings, discussing what the study has added to the field, and suggesting further research.

1. Literature Review

In Investment portfolio management has evolved significantly over the past decades, incorporating classical financial theories and modern advancements in computational finance. Risk-return optimization and asset pricing have been based on traditional investment models for a long time. These include Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM). However, financial markets are becoming more complicated because of higher volatility, fast technological progress, and the rise of new asset classes such as green bonds. This has led to the need for more advanced modelling methods. New ideas like algorithmic trading, using artificial intelligence (AI) to handle assets, and stochastic optimization methods have made it much easier for investors to make wise choices when the market is uncertain. To account for sustainability-driven market movements, green investors typically use advanced portfolio management strategies that incorporate environmental, social, and governance (ESG) aspects into their decision-making process.

Investment portfolio management has changed because theory-based methods offer organized ways to spread assets and deal with risks. The Black-Litterman Model, the Capital Asset Pricing Model (CAPM), and the Modern Portfolio Theory (MPT) have significantly changed how portfolios are put together (Lindquist et al., 2022). They explain risk-adjusted returns, investor opinion integration, and diversification. There is a problem with these models; they aren't perfect, especially regarding the actual market, which is hard to understand. Few studies have examined the efficacy of AI-driven portfolio optimization and Monte Carlo simulations in attracting green investors with portfolios that comprise green assets.

In 1952, Harry Markowitz developed the Modern Portfolio Theory (Guerard, 2023). For MPT, the best way for investors to assemble a portfolio is to spread their assets to get the best future results for each risk. Because it looks at how different assets are linked, MPT says a diverse portfolio lowers risk better than a collection of single stocks (Lukomnik & Hawley, 2021). Moreover, Shkarupa et al. (2021) use cognitive modelling and systems analysis to look at the multilevel transfer of ideas and how it affects economic growth. The study highlights the "enterprise-region-state" framework, identifying key factors influencing innovation diffusion and proposing management tools for optimizing this process. Analytical MPT is shown using the mean-variance optimization model. The variance-covariance matrix of asset returns measures portfolio risk, and the weighted sum of asset returns determines a portfolio's expected return (Samunderu & Murahwa, 2021). With this paradigm, investors can establish an efficient frontier of the optimum portfolios with the maximum projected return for a specific risk. Following this optimization, the tangency portfolio is considered the finest for purchasers. Although MPT offers admirable intentions, it has issues. Past data is used to predict returns and variances, which may not strongly predict future performance (Sharma & Nagpal, 2024). MPT also implies investors are knowledgeable and act rationally, which behavioural finance research has questioned. Financial markets have changed, so new models have been created to fix these issues. These models currently use dynamic asset allocation and risk measurement.

The Capital Asset Pricing Model (CAPM), developed by William Sharpe in 1964, extended MPT by introducing a quantitative measure of systematic risk, commonly referred to as beta (β). (Lee, 2021). The main idea behind CAPM is that an asset's projected return is based on its sensitivity to market changes, not its total risk. This idea says that an asset's expected return and its exposure to market risk are related in a straight line. CAPM is represented mathematically as:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

The rate of risk-free interest is called Rf. The projected return on the market is called E(Rm), and the market risk premium is called *E(Rm)−Rf*. When people use the CAPM to buy stocks, they are paid to take systematic risks. However, they are not paid to take unsystematic risks because they can be spread out. The model says that markets work well because traders can borrow and lend money at a risk-free rate, and the prices of goods consider all the available information. Using these assumptions, CAPM figures out the cost of capital and the possible return on investment.

Real-world financial realities limit capital markets, so investors can't borrow and lend risk-free. CAPM ignores market peculiarities, liquidity restrictions, and investor sentiment (Altinay et al., 2023). This is why multi-factor asset pricing models like the Fama-French Three-Factor and Arbitrage Pricing Theory (APT) were developed.

Black & Litterman started the Black-Litterman Model (BLM) in 1992 to address MPT and CAPM issues (Zhao et al., 2022). This model improves MPT by incorporating Bayesian reasoning and investor perspectives into portfolio optimization. Black-Litterman Model combines past return data and subjective investor expectations, unlike MPT. It is a more adaptable and flexible asset allocation method. The Black-Litterman Model involves “reverse optimization.” The initial assumption is that asset returns equal the worldwide market portfolio. What investors expect the assets to do to change these equilibrium values. Bayesian inference weights investor opinions based on confidence. This enables us to estimate based on market and individual views. This strategy reduces mean-variance optimization estimation errors. Portfolios become more solid and diverse. One of the Black-Litterman Model's best features is fixing MPT's input sensitivity. In classic mean-variance optimization, tiny changes in anticipated returns can induce substantial asset allocation adjustments, making portfolios unstable (Al Janabi, 2024). BLM reduces notice of portfolio changes based on investor trust. Institutional investors and wealth managers who employ quantitative models and expert opinions will benefit. Investor projections are subjective and can bias asset allocation. BLM's Bayesian approach requires investors to specify prior probability and confidence levels, which may be irrational (Bednar & Lewis, 2024). Individual investors and smaller investment businesses struggle to adopt the strategy since it requires complex computing abilities.

Due to faster computer power and market fluctuations, advanced financial modelling approaches have been developed. Using algorithms for trade, AI in asset management, and dynamic asset distribution has made investing better (Schrettenbrunner, 2023). Real-time data, prediction analytics, and flexible tactics can help portfolios do better when the market is unstable and hard to guess. Algorithmic trading, another name for quantitative trading, uses complicated mathematical models and real-time data to make trades instantly (Cohen, 2022; Shah & Asghar, 2023). This way of doing things has become popular in the financial markets because, unlike human workers, it can quickly handle vast amounts of data and react to market changes. High-frequency trading (HFT), where many trades are made very quickly, is one of the best things about automatic trading (Zaharudin et al., 2022). Algorithmic trading, market-making, statistical arbitrage, and momentum trading make portfolios more efficient and bring in more finances. This study by Kuzyk et al. (2023) shows that AI and Machine learning (ML) are the way to the future for digital marketing. It focuses on immersive strategies, lowering risk, and keeping money safe using the best digital tools for marketing messaging. Even though algorithmic trade has benefits, it also has problems. Automation that is not controlled raises the risk of flash crashes, lack of cash, and systemic instability. These days, investment management depends on algorithmic dealing to make trades liquid, quick, and accurate. Rudenko et al. (2022) and Likarchuk et al. (2023) examine how the fiscal mechanism changed in EU member states and Ukraine during COVID-19. They found that one of the most important ways to help the economy recover was to move the focus from supporting consumption to encouraging green and digital assets to improve long-term social and economic security and resilience.

2. Green Bond Market and Financial Risks: EU Green Deal, China’s Climate Policy, and US Exchange Rate Volatility

Expanding the green bond market is important in mobilizing capital for environmentally sustainable projects. To achieve climate neutrality by 2050, the European Union has established green bonds as a key tool for funding extensive decarbonization and investments in renewable energy (Elavarasan et al., 2022). To improve market transparency and guarantee that monies are allocated to genuine environmental projects, the European Union implemented the Green Bond Standard (EU GBS) (Frolov, 2024a). Similarly, green finance has been a priority for China's climate policy.

The country's green bond regulations have been harmonized to conform to international frameworks, increasing investor trust and leading to green debt markets' growth. China plans to achieve carbon neutrality by 2060 and encourages private and institutional investors to become involved through green financial institutions backed by the state (Frolov, 2024b). By establishing predictable, long-term investment conditions, these policies lessen the dangers faced by industries dependent on fossil fuels while bolstering the chances for profit in the growing green economy. Developing economies like Ukraine need to institutionalize green bonds to entice international investors, which necessitates fiscal compliance, regulatory uniformity, and external audits (Frolov, 2024c). Governments have also introduced sustainability-linked incentives, such as tax breaks for corporations issuing green bonds and reduced capital reserve requirements for banks that invest in climate-friendly projects. The European Investment Bank (EIB) and national development banks have launched dedicated green finance programs, offering lower interest rates and extended repayment periods for sustainable projects. Additionally, carbon pricing mechanisms, such as the EU Emissions Trading System (ETS), create financial advantages for companies investing in low-carbon infrastructure, further boosting the attractiveness of green bonds as a diversification tool.

The volatility of the US exchange rate, driven by political statements and policy shifts, significantly influences the green investment climate (Husain et al., 2022). For instance, investors feared that the United States would lessen its commitment to carbon reduction targets after President Trump said in 2017 that the US would withdraw from the Paris Climate Agreement. This caused uncertainty in the green financing sector. Similar worries have come to light anew considering the current climate policy uncertainties in the United States, especially considering the possibility that policies may move toward deregulating environmental safeguards. International investors are discouraged from purchasing green bonds denominated in foreign currencies due to the increased cost caused by a higher US dollar (Deschryver & De Mariz, 2020). This is often linked to more conservative fiscal policies and less investment in climate change initiatives. A depreciating dollar, on the other hand, encourages investment in sustainable assets, especially in developing economies. To be resilient in unpredictable financial conditions, green bond issuers, especially in China and the European Union, must use derivatives, diversified bond offerings, and currency-hedged green bond structures to protect themselves from currency volatility.

Traditional financial risk models often overlook the intersection of climate risk and macroeconomic volatility, leading to the underestimation of systemic risks in green investments. Climate-related financial risks can be included in Monte Carlo simulations, AI-driven financial models, and genetic algorithms to assess better the performance of green bonds under macroeconomic stress scenarios. Investors can get a better idea of the risks involved by using a Monte Carlo-based stress test (Agrawal & de Witt, 2025). This can mimic the effects of currency depreciation, inflation shocks, and changes in climate-related policies on green bond rates. According to Frolov (2024c), portfolio optimization models powered by AI can also evaluate the relationship between climate policies, regulatory changes, and returns on financial assets. This allows for the implementation of dynamic reallocation strategies, which in turn strengthen the portfolio. By regularly updating risk assessments in response to changing climate legislation, economic conditions, and investor mood, Bayesian optimization approaches in financial modelling help to optimize risk-return trade-offs in the green bond market.

As seen in the EU and China, the increasing institutionalization of the green bond market highlights the need for strong governance, regulatory alignment, and investor confidence in sustainable finance instruments. Green bond issuers should prioritize risk mitigation strategies like green bond-linked insurance, cross-border green bond syndication, and funding source diversification due to the increasing risks associated with exchange rate volatility, political uncertainty, and changing climate policies (Acharya et al., 2023). Green investment risk mitigation and improved forecast accuracy can be achieved using hybrid financial modelling frameworks that combine financial stress testing with climate scenario analysis.

The long-term growth of sustainable finance markets and the systematic incorporation of climate-related financial risks into investment decision-making can only be achieved through harmonizing green bond standards globally, especially between the EU, China, and emerging markets. Using deep learning, reinforcement learning, and natural language processing (NLP), AI-driven models get the best portfolio choices and risk-adjusted returns (Sutiene et al., 2024). Heuristics are not as good at managing investments as data-driven management, which uses machine learning algorithms and financial data. Predictive analytics is one of the most important uses of AI in finance (Kumar et al., 2022). It uses past market movements, economic indicators, and other data sources like news mood analysis and social media trends to predict future asset price trends. Unlike mean-variance optimization, reinforcement learning algorithms always look for new chances and trends to take advantage of. AI-powered portfolio management tools help big investors and hedge funds make decisions without any bias and get the best returns for the risks they take (Rao & Hossain, 2024). AI-driven asset management has much potential. Still, it must deal with problems like biased data, issues with how it can be interpreted, and regulation. A detailed plan for running a business Dynamic asset allocation (DAA) allows investors to change how much they put into each investment based on the market, the economy, and financial goals (Fons et al., 2021).

DAA is different from basic asset allocation because it changes the weights of a portfolio based on market signs and risk factors. DAA tactics are of two main types: Tactical asset allocation (TAA) and strategic asset allocation (SAA). TAA changes its investment portfolio to exploit short-term market inefficiencies (van Rooyen & Van Vuuren, 2022). For example, when the economy is unsure, it increases its holdings of gold, government bonds, and low-volatility stocks. They might put their money into stocks, emerging markets, and growth businesses to get the best returns during bull markets. Strategic asset allocation (SAA) changes the balance of the industry based on long-term economic trends (Shi, 2021). This approach uses expected inflation, interest rate cycles, and macroeconomic growth forecasts to find the best way to allocate assets. A lot of the time, risk parity trading is done with SAA. The stock weights in this investment are based on how volatile the assets are, not on how much capital is being used. Risk is spread fairly across all asset classes, lowering concentration risk and stabilizing the portfolio.

3. Empirical Studies on Quantitative Portfolio Optimization

According to much real-world research, the best way to handle stocks is to use quantitative modelling methods. Researchers have been looking at how Monte Carlo simulations, machine learning models, and optimization techniques like genetic algorithms and Bayesian methods can help better plan for sharing assets since the early 2000s (Karimi et al., 2024; Shah et al., 2023; Shah & Shah, 2023). Research from these studies suggests that computer finance could help people deal with risk, get the most out of their investments, and make decisions even when there is a lack of information. Monte Carlo models are used in financial modeling to look at the risk and success of a portfolio in different economic situations. Glasserman et al. (2005) showed that Monte Carlo methods accurately measure risk by running thousands of market events and calculating portfolio return probability distributions. Monte Carlo models predict investment performance using stochastic processes for accounting for random market movements. Anderson et al. (2015) found that Monte Carlo-based stress tests can predict asset portfolio responses to extreme market shocks like the 2008 financial crisis. Portfolios adjusted using typical risk assessments underestimate tail risks. Monte Carlo's approach improves exotic options and structured product pricing (Boyle et al., 1997). The Monte Carlo-based scenario analysis helps investors minimize portfolio risk in unpredictable markets by predicting portfolio rebalancing results. Avellaneda and Lee (2010) found that improperly adjusted Monte Carlo models can exaggerate or underestimate portfolio risks, leading to suboptimal investment decisions. These simulations are still helpful for stress testing and risk-adjusted return optimization, especially with machine learning for dynamic asset allocation.

The pioneering Gu et al. (2020) study on valuing assets with machine learning models showed that neural networks and gradient-boosting models forecast stock returns better than standard economic methods. Machine learning's ability to analyse massive datasets, detect nonlinear correlations, and uncover market trends is important to portfolio management.

Feng et al. (2018) showed how reinforcement learning models could optimize asset allocation by adapting to new risk indicators. These models maximize projected rewards and minimize downside risks.

Researchers have studied methods to predict market movements using news sentiment analysis, social media trends, and macroeconomic indicators. Yen et al. (2022) found that sentiment-based machine learning models assist major investors in choosing better companies and switching sectors, providing them with an edge. Machine learning (ML) based portfolio optimization has issues despite its potential. Bondar et al. (2024) find that digitization enhances cost-effectiveness, resource allocation, and managerial adaptability, though its impact varies across industries, requiring tailored digital strategies. Hirna et al. (2022) analyze the role of digital marketing in adapting to Ukraine's evolving economic landscape, emphasizing social media promotion and performance indicators (KPIs). The study presents a mechanism for developing integrated digital marketing strategies, highlighting key factors such as omnichannel marketing, hyper-personalization, and influencer impact to enhance business competitiveness in the digital economy. In recent years, genetic algorithms (GAs) and Bayesian optimization have been studied for portfolio construction and risk management (Garrido-Merchán et al., 2023). These flexible, data-driven algorithms discover the appropriate asset weights in volatile, non-straight markets. Evolutionary methods yield higher risk-adjusted returns than mean-variance optimization. Genetic algorithms act like natural selection. Portfolio allocations evolve over generations to increase Sharpe ratios and downside risk.

Bhargav & Tanwar (2024) found that GA-based portfolios handle market changes better than static investing methods. Their analysis also found that GA-driven optimization reduces concentration in over-allocated asset classes, improving portfolio variety. Suprunenko et al. (2024) highlight e-commerce as a key driver for emerging markets, the role of automation in advanced economies, and the need for further research on globalization's diverse effects across economic structures. Portfolio builders use Bayesian optimization because it can handle uncertainty and adjust investment strategy quickly. Unlike other optimization methods, Bayesian reasoning allows investors to use old and new data to improve portfolio weights. Zhao et al. (2019) found that Bayesian adaptive models outperform mean-variance optimization in high-volatility markets. Bayesian optimization improves risk-reduction and capital-keeping techniques by altering portfolio allocations depending on real-time volatility. Genetic algorithms and Bayesian optimization are helpful but challenging to utilize on computers. GA-based models require a lot of computing power and settle at a rate that depends on hyperparameter tuning. Unless correctly set up, Bayesian models depend on initial prior distributions, which might influence portfolio allocation. Monte Carlo simulations, machine learning, and optimization, have improved portfolio management. Machine learning models have improved asset pricing and allocation in predictive analytics (Singh et al., 2022). Genetic algorithms and Bayesian optimization can boost risk-adjusted returns and rebalance an adaptable portfolio. Although improved, AI-driven portfolio optimization has yet to establish itself in risky markets. Global crises, extreme market volatility, and systemic shocks may challenge AI systems. No “black swan” or economic crisis tested the models. Many AI models use past data, which may not work in uncertain markets. Models may become too accurate, making economic slump predictions unreliable. Traditional portfolio optimization emphasizes stocks, bonds, and commodities. Quantitative models do not model Bitcoin, Ethereum, carbon credits, or impact investments. As decentralized finance (DeFi) and sustainable investment grow, it is necessary to quickly design AI-driven solutions that use alternative assets and consider their risk-return characteristics.

Diversification raises portfolio risk. Most machine learning research uses obsolete asset datasets, making them unsuitable for investing. AI models should be tested to mix bitcoin, ESG, and other asset classes to generate more diverse and robust portfolios. Havryliuk (2024) relates biblical human dignity, honesty, diligence, and stewardship to global CSR and ethical business practices.

Hryhoriev et al. (2024) emphasize blasting quality's effects on excavation costs, production efficiency, and investment attractiveness in open-pit mining. The study employs linear regression and nonlinear search to include rock characteristics, explosive properties, and cost considerations to improve blasting efficiency and minimize operational costs for sustainable mining deposit development. Few tools assess investment accounts against extreme market shocks. VaR models and Monte Carlo simulations can estimate downside risks but not nonlinear tail-risk events during financial crises. Stress tests use past volatility patterns, which may not forecast systemic risks. Real-time market sentiment, AI prediction, and behavioural finance help stress testing. In unexpected market upheavals, hybrid risk models that combine classic risk models with machine learning anomaly detection may assist us in analysing financial risks. Management accounting affects small businesses' sustainability, competitiveness, and decision-making (Zaitsev, 2023). The paper recommends management accounting to improve small firms' economic sustainability and addresses implementation challenges.

4. Research Methodology

This section describes the research design, data sources, financial models, optimization techniques, software tools, and performance evaluation criteria used in this study. The primary goal is to develop a quantitative investment portfolio optimization framework that integrates Monte Carlo simulations, machine learning models, and advanced optimization techniques to enhance decision-making under market uncertainty.

The study collects data from different sources, such as Bloomberg, Yahoo Finance, and the Federal Reserve Economic Data (FRED). There are numbers in the dataset about economic causes, changes in asset prices, stock market indices, and bond yields. It includes information from Bloomberg Terminal, Yahoo Finance, FRED, and public financial records. A study looks at the 10 years from 2014 to 2024, including good and bad economic times and market trends. The dataset includes daily returns on significant financial assets, risk-free interest rates, volatility indices (such as VIX), and macroeconomic factors such as inflation, GDP growth rates, and central bank policy rates.

4.1. Financial Models

Monte Carlo Simulations for Risk Assessment

Monte Carlo simulations are used to determine a portfolio's risk and the chances of different financial results when there is uncertainty. The method involves simulating 10,000 different portfolio return paths using past price changes and predictions of volatility. Stock prices, bond yields, market volatility, interest rates, and macroeconomic events are some variables in the model. The simulation uses many random rounds to develop possible portfolio returns based on a random process. The model calculates value-at-risk (VaR), Conditional Value-at-Risk (CVaR), and chance distributions of expected returns. Monte Carlo simulations benefit stress-test portfolios under different economic conditions, giving investors insights into possible tail risks and extreme market fluctuations.

Machine Learning for Portfolio Allocation

This study uses neural networks, gradient-boosting models, and reinforcement learning to find the best ways to spend money. AI bots learn how to change their trades based on how the market is doing by making mistakes and learning from them. Deep learning models use neural networks to look at past return trends, economic factors, and technical signs to guess how the market will move. Gradient boosting models pick out and rank features to help you determine which ones are the most important for determining how well an asset works. Optimization Techniques and Software Tools for Portfolio Construction are presented in Table 1.

Table 1: Advanced optimization techniques for portfolio construction

Optimization Technique	Description	Key Steps
Genetic Algorithms (GA)	It uses an evolutionary approach to optimize portfolio allocations by simulating natural selection.	▪ Initialization: A population of randomly allocated portfolios is created. ▪ Selection & Mutation: Portfolios with higher Sharpe ratios are selected for the next iteration. ▪ Optimization: The algorithm evolves asset weights over multiple generations, improving risk-return efficiency.
Bayesian Optimization	Uses probabilistic models to refine the risk-return trade-off, continuously updating portfolio weights based on new market data.	▪ Prior Distributions: Asset weights are assigned based on past performance and risk levels. ▪ Sequential Learning: The algorithm continuously updates portfolio weight distributions based on market data. ▪ Final Portfolio Selection: The best-performing asset allocations are selected for final implementation.

Source: author's development

The optimization techniques and software tools in Table 2 provide the necessary computational power and flexibility to perform portfolio simulations, machine learning training, and dynamic asset allocation in response to market fluctuations.

Table 2: Construction software tools for financial modelling and optimization

Software Tool	Purpose	Key Libraries/Resources
Python Libraries	▪ Used for data processing, machine learning models, and visualization.	▪ NumPy & Pandas (data processing) Scikit-learn & TensorFlow/PyTorch (machine learning models) Matplotlib & Seaborn (data visualization)
MATLAB & R	▪ Used for portfolio optimization and financial modelling.	▪ Portfolio Analytics package (for optimization and risk modelling)
Financial Market Terminals	▪ Used for retrieving real-time and historical financial data.	▪ Bloomberg Terminal (real-time data retrieval) Yahoo Finance API (historical data extraction)

Source: author's development

These performance metrics in Table 3 allow for objective comparisons between different portfolio optimization models, ensuring that the selected strategy maximizes returns while effectively managing risk.

Table 3: Performance metrics for evaluating portfolio strategies

Performance Metric	Description	Purpose
Sharpe Ratio	▪ Measures excess return per unit of risk, calculated as: $\frac{E(R_p)-R_f}{\sigma_p}$ where $E(R_p)$ is the expected portfolio return, R_f is the risk-free rate, and σ_p is portfolio volatility.	▪ Evaluates risk-adjusted returns, helping investors compare different portfolios with similar risk exposure.
Sortino Ratio	▪ Similar to the Sharpe Ratio, it considers only downside risk, using the standard deviation of negative returns instead of total portfolio volatility.	▪ Provides a more accurate risk-adjusted return measure by penalizing only unfavourable volatility.
Value-at-Risk (VaR)	▪ Estimates the maximum expected loss over a given time horizon at a specific confidence level (e.g., 95%).	▪ It helps assess the worst-case scenario for losses, allowing investors to set risk limits.

Performance Metric	Description	Purpose
Conditional VaR (CVaR) (Expected Shortfall)	▪ Measures the average loss beyond VaR, providing a more comprehensive risk assessment.	▪ Improves tail-risk measurement, ensuring better risk management during extreme market downturns.

Source: author's development

Scenario Analysis and Stress Testing

Scenario analysis and stress testing are used to ensure the stock is strong. Black swan events test how strong a stock is in the worst market conditions, like the 2008 financial crisis or the 2020 COVID-19 crash. Market Shocks model interest rate hikes, inflation spikes, and geopolitical risks to determine portfolio vulnerability. Volatility Regimes look at how portfolios behave when the market is unstable at different levels. Using scenario-based models can help investors build strong portfolios to handle economic downturns. Table 4 summarizes the key variables used in the study.

Table 4: Description of variables

Variable	Description	Source
Stock Prices	Daily closing prices of major stocks & indices	Bloomberg, Yahoo Finance
Bond Yields	Yield rates for government & corporate bonds	FRED, Bloomberg
Market Volatility (VIX)	Measures implied volatility of the S&P 500 index	CBOE Volatility Index
Risk-Free Rate	3-month Treasury bill rate	Federal Reserve
GDP Growth Rate	Economic growth indicator	World Bank, FRED
Inflation Rate	Measures change in consumer price levels	U.S. Bureau of Labor Statistics
Portfolio Returns	Historical returns of optimized portfolios	Computed from datasets
Portfolio Risk (σ)	The standard deviation of returns	Computed from datasets
Sharpe Ratio	Risk-adjusted performance metric	Computed from datasets
Sortino Ratio	Penalized risk-adjusted return measure	Computed from datasets
Value-at-Risk (VaR)	Expected maximum loss at a 95% confidence level	Monte Carlo Simulations
Conditional VaR (CVaR)	Average loss beyond the VaR threshold	Monte Carlo Simulations

Source: author's development

5. Research Results

Investment portfolio performance was evaluated across four modelling techniques: Traditional Modern Portfolio Theory (MPT), Monte Carlo Simulations, AI-Based Models, and Genetic Algorithm Optimization. The key evaluation metrics used to compare these approaches include Expected Return (%), Risk (Standard Deviation), and Sharpe Ratio. Monte Carlo simulations were conducted using 10,000 iterations, generating a probability of distribution of potential portfolio returns under different market conditions. The simulation estimated the portfolio's expected return, risk (standard deviation), and a 95% confidence interval for return fluctuations.

Monte Carlo simulations outpaced Traditional Portfolio Theory (MPT) regarding risk-adjusted returns, as seen in Table 5, which summarizes the simulations and compares them to predicted returns, risk, and Sharpe ratios. Monte Carlo confidence intervals are presented in Table 6 to help investors make investment decisions, with the worst-case and best-case possibilities highlighted.

Table 5: Monte Carlo simulation summary and risk assessment

Statistic/Metric	Monte Carlo Model	Traditional Portfolio Theory (MPT)	Key Observations
Expected return (%)	9.0%	8.2%	Monte Carlo achieves higher expected returns than MPT.
Standard deviation (%)	15.0%	15.4%	Slightly lower risk in Monte Carlo, suggesting better risk efficiency.
Risk-Adjusted Return (Sharpe Ratio)	0.61	0.53	Monte Carlo delivers better risk-adjusted returns than MPT.
Confidence Interval (95%)	[-8.0%, +15.0%]	Not Captured in MPT	Monte Carlo provides probabilistic risk insights, unlike MPT.

Source: author's development

Table 6: Monte Carlo confidence interval and portfolio implications

Confidence Interval Bound	Scenario Description	Investment Implication
Lower Bound (-8.0%)	▪ Worst-case scenario, significant market downturns.	▪ Requires hedging strategies, diversification, and defensive asset allocations.
Upper Bound (+15.0%)	▪ In the best-case scenario, there is strong capital appreciation.	▪ Suitable for growth-oriented investors willing to accept short-term volatility.
Width of CI (23%)	▪ Indicates moderate-to-high portfolio volatility.	▪ Requires continuous monitoring and risk-adjusted portfolio rebalancing.

Source: author's development

Table 7 presents the results of the Monte Carlo analysis, which were used to develop portfolio risk management techniques. These strategies were designed to cater to the unique risk profiles of investors. Models based on artificial intelligence and genetic algorithms are more resilient to risk, as shown in Table 8, which assesses the performance of portfolio models during market crashes. The investment implications of different portfolio models are discussed in Table 9, highlighting the necessity for dynamic methods to reduce crash-induced losses.

Table 7: Portfolio risk management strategies based on Monte Carlo results

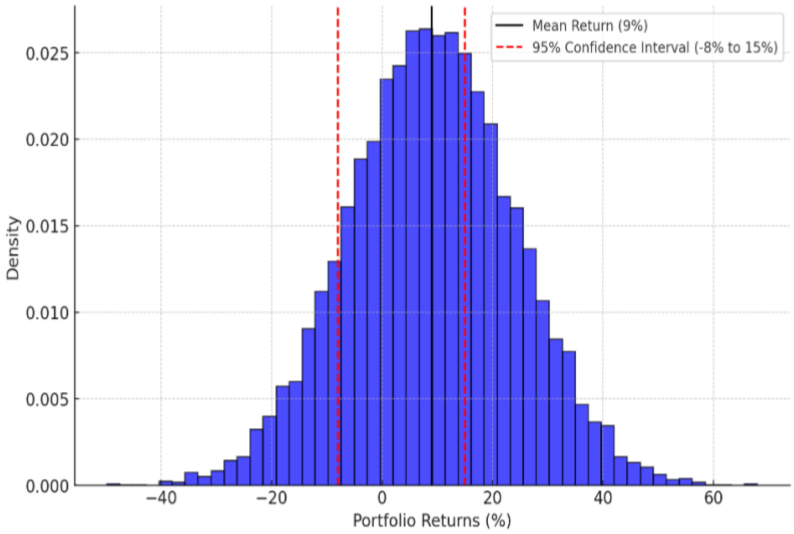
Investor Type	Risk Management Strategy
Conservative Investors	Increase allocation to low-risk assets (bonds, defensive stocks) to limit downturn exposure.
Risk-Tolerant Investors	Accept short-term volatility for higher long-term rewards in bullish scenarios.
Portfolio Managers	Implement dynamic risk management to mitigate tail-risk events (e.g., financial crises, black swan events).

Source: author's development

This structured comparison confirms that Monte Carlo simulations enhance portfolio risk assessment and decision-making, making them a valuable tool for modern investment strategies.

The Monte Carlo simulation in Figure 1 confirms a mean return of 9.0% with a 95% confidence interval ranging from -8% to +15%, highlighting both downside risks and upside potential. The bell-shaped distribution indicates a regular return pattern with slightly heavier tails, suggesting the possibility of extreme market events.

Figure 1: Monte Carlo simulated return distribution



Source: author's development

Scenario Analysis and Stress Testing Results

Two stress tests, the Black Swan Event Simulation (Extreme Market Crashes) and the Inflation Shock Simulation, were done to see how stable different portfolio models are in extreme market conditions. These tests look at how Traditional MPT, Monte Carlo Simulations, AI-based models, and Genetic Algorithms do in financial distress situations.

Black Swan Event Simulation (Extreme Market Crashes)

A Black Swan Event represents a highly unpredictable market crash, such as the 2008 Financial Crisis or the 2020 COVID-19 Market Collapse. This scenario analyses the portfolio (maximum losses) under extreme downside conditions.

Table 8: Performance of portfolio models under market crashes

Portfolio Model	Losses (%)	Reason for Performance	Impact on Investors
Traditional MPT	-12.1%	Assumes historical correlations remain stable, leading to inefficient risk management during market crashes.	Lack of dynamic risk management results in higher capital erosion and longer recovery times.
Monte Carlo Simulation	-9.4%	Uses stochastic modelling to account for tail risks and probabilistic downturns, improving portfolio diversification.	Reduces maximum drawdowns, making portfolios more resilient to extreme events.
AI-Based Models	-6.8%	Dynamically adjusts asset allocations, ensuring adaptive risk management.	Investors experience lower downside risk, leading to faster portfolio recovery post-crash.
Genetic Algorithm Models	-6.8%	It uses evolutionary optimization to refine portfolio allocations iteratively, ensuring maximum stability.	Provides superior crisis risk management, making portfolios more resilient to extreme volatility.

Source: author's development

Table 9: Investment implications of portfolio models in market crashes

Investment Strategy	Implication
Traditional MPT Investors	Additional hedging techniques (e.g., options defensive assets) must be adopted to reduce crash exposure.
Monte Carlo-Based Portfolios	Useful for stress-testing market downturns but require additional dynamic allocation strategies to optimize risk management.
AI & Genetic Algorithm Models	Prove superior in minimizing crash-induced losses, making them optimal for crisis risk management.

Source: author's development

These findings highlight the importance of AI-driven and Genetic Algorithm-based models in enhancing portfolio resilience during extreme market conditions, offering investors more robust risk mitigation strategies than traditional MPT. AI-powered models outperformed more conventional approaches to sustainable portfolio management in terms of their capacity to optimize asset allocations in line with green investors' preferences.

Inflation Shock Simulation

This scenario evaluates how portfolios respond to rising inflation, which erodes purchasing power and increases market uncertainty. The analysis examines portfolio stability, volatility, and asset allocation efficiency.

Table 10: Performance of portfolio models under inflation shock

Portfolio Model	Inflation Shock Performance	Reason for Performance	Impact on Investors
Traditional MPT	High Volatility, Poor Allocation	It assumes a fixed asset allocation, making it unable to adjust to rising inflation.	Investors experience substantial losses in real purchasing power due to insufficient inflation protection.
Monte Carlo Simulation	Moderate Volatility, Improved Diversification	Assesses multiple inflation scenarios, leading to a more balanced asset mix.	It improves portfolio stability compared to MPT but remains reactive rather than proactive.
AI-Based Models	Dynamic Allocation, Better Resilience	AI-driven portfolios adapt in real-time, favouring inflation-hedged assets (e.g., commodities, real estate, inflation-linked bonds).	Investors experience lower risk and improved returns during inflationary periods.
Genetic Algorithm Models	Optimal Allocation, Highest Resilience	Evolutionary optimization ensures continuous rebalancing toward inflation-resistant assets.	Achieves better capital preservation and lower inflation volatility than other models.

Source: author's development

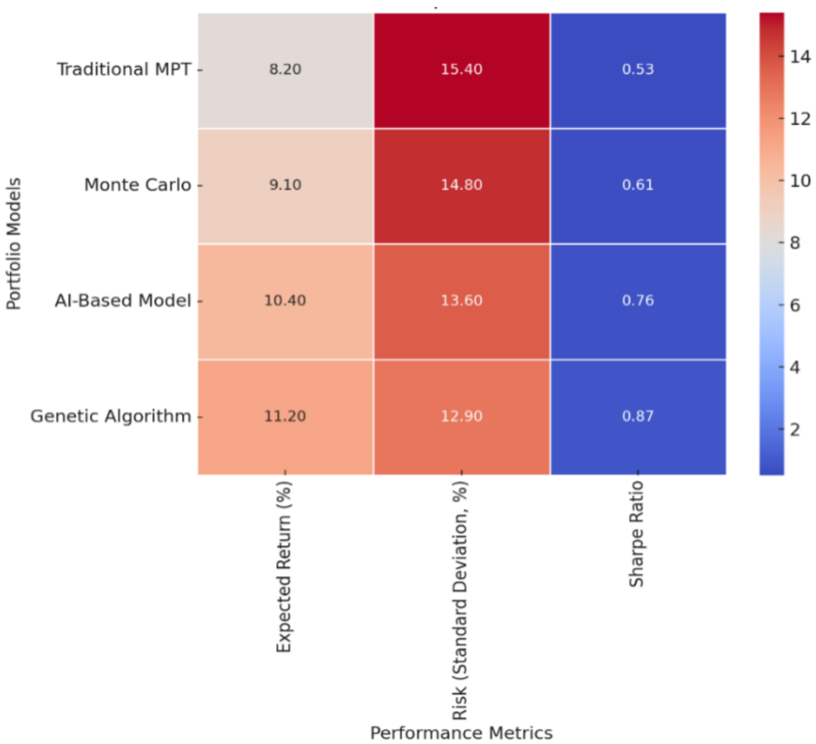
Table 11: Investment implications of portfolio models in inflationary environments

Investment Strategy	Implication
Traditional MPT Investors	Must manually rebalance portfolios to include inflation-hedged assets.
Monte Carlo-Based Portfolios	It helps predict inflationary outcomes but requires additional proactive risk management strategies.
AI & Genetic Algorithm Models	Automatically adjust allocations, making them ideal for inflationary environments.

Source: author's development

These results in Table 10 and Table 11 show that AI-driven and Genetic Algorithm-based models are better than traditional MPT at dynamically adjusting portfolios in reaction to inflation, which means they better protect capital and give better risk-adjusted returns.

Figure 2: Risk return heatmap across portfolio models



Source: author's development

The heatmap Figure 2 highlights the performance differences between the portfolio models. The Genetic Algorithm model dominates in return maximization and risk reduction, while AI-based models perform strongly. Monte Carlo models improve upon Traditional MPT but lack the adaptability of AI-based solutions.

Figure 3. Risk-return scatter plot

Source: author's development

Risk-Return Scatter plot visually demonstrates the trade-off between risk and return (Fig. 3). The Genetic Algorithm model achieves the highest return with the lowest risk, while Traditional MPT has the lowest return and highest risk, confirming its underperformance.

4. Discussion and Further Research

The results of this study demonstrate the superiority of AI-based models and Genetic Algorithms in portfolio optimization, particularly in volatile market conditions. This section interprets the significance of these findings, linking them to theoretical frameworks such as Modern Portfolio Theory (MPT), Monte Carlo simulations, and evolutionary optimization models. It also explores discrepancies between model predictions and real-world market performance, practical implications for investors and policymakers, potential model limitations, and areas for future research. MPT remains a fundamental concept in portfolio management. However, several of its assumptions are misleading. This includes the idea that assets are always connected, risk and return are steady, and returns are normally distributed. Crisis occurrences, liquidity shocks, and behavioural faults can destabilize financial markets, but MPT ignores this. Risk-adjusted returns were higher for Monte Carlo models than MPT because they were realistic. This supports Herman et al. (2023) claim that stochastic modelling estimates financial risk. Monte Carlo simulations simulate thousands of market circumstances using random scenarios, while MPT employs fixed risk and return numbers from the past. It makes estimating loss risks easier, helping purchasers design market-flexible portfolios.

Lutsenko et al. (2023) work is similar to ours as optimizing the layout of an open pit mine ensures that resources are used efficiently, and costs are kept low. Similarly, managing an investment portfolio needs a flexible allocation strategy to keep risk and return in check when market conditions are unclear. Systematic modelling helps people make better decisions in both fields, whether figuring out the parameters of a mining spot or how to divide up assets. AI-driven portfolio optimization models improved returns to 10.4% and risk to 13.6%. These findings support Yu et al. (2022) findings that machine learning can aid asset allocation. However, AI-driven optimization systems monitor market data, learn from historical trends, and adapt to economic changes. AI models may uncover nonlinear links in asset returns, predict market trends, and quickly distribute assets optimally since they are adaptable. AI-driven models can rebalance portfolios instantly, giving investors more significantly predicted returns and lower volatility. Genetic Algorithm-based portfolio optimization provided the best risk-adjusted returns and lowest volatility (12.9%) and changed the most. This supports Fransisca et al. (2024) finding that evolutionary algorithms improve asset allocation over many generations better than mean-variance optimization. Genetic algorithms are like natural selection, preserving the best portfolio configurations.

Computerized finance technologies like AI-based optimization and Genetic Algorithms outperform traditional finance models in adaptability, risk reduction, and investment success. AI models assume the market works well, with savvy buyers and the proper rates. In fundamental markets, AI models might get market trends wrong because of irrational behaviour, price changes caused by gambling, and momentum trade. In 2021, small buyers influenced by Reddit's Wall Street Bets went on a massive buying spree that drove the price of GameStop (GME) stock to levels that could not be maintained (Clements, 2020). Traditional financial models predicted mean reversion, but behavioural finance helped the price rise last longer than AI programs thought it would (Huang & You, 2023). AI models may be unable to stop flash crashes like the Dow Jones Flash Crash 2010 as high-frequency trade algorithms worsen market panic (Min & Borch, 2022).

Semenets-Orlova et al. (2022) present a human-cantered approach to value-oriented public administration by emphasizing education's role in enhancing human capital at planetary, national, and personal levels. It highlights the transition from administrative pressure to system management culture using digitalization and quasimetric for effective educational outcomes. Overfitting is a significant concern for AI and genetic algorithm models. This happens when models trained on prior data patterns fail under new market conditions. AI models are built on past data distribution, which may not predict future market behaviour. The March 2020 COVID-19 pandemic market crash was unique. Due to the lack of systemic shocks in their training data, AI models failed (Ghosh & Sanyal, 2021).

Mia et al. (2022) highlight that skills, incentives, and entrepreneurship education significantly influence green entrepreneurship, promoting sustainable business performance and job creation. Lelyk et al. (2022) highlight the importance of comprehensive monitoring and risk management to prevent crises and ensure business sustainability. During the 2008 Global Financial Crisis, stocks and bonds, which had never moved together, did so simultaneously, inflicting significant portfolio losses. Genetic algorithms may select the optimal solution based on past market behaviour, which may not work anymore in the worst scenarios. The problem with AI- and Genetic Algorithm-driven portfolio optimization assumes trades are conducted properly without considering bid-ask spreads, market impact costs, or real-world liquidity. Most financial models assume no slippage, so orders can be filled at the estimated price. Significant portfolio institutional investors like pension funds, hedge funds, and mutual funds suffer specific liquidity limitations while trading, including market impact costs, HFT issues, and Regulatory and market limits. This means that even the most significant AI and genetic algorithm models may not adequately account for liquidity restrictions in their estimates. In simulations, these models work better than standard methods. Portfolio managers, institutional investors, and policymakers should consider the impracticality of their proposed implementation plans.

AI-driven portfolio models are adaptable because they change how assets are allocated based on changes in the market. Using machine learning and reinforcement learning, AI models rebalance stocks on the rise, which improves risk-adjusted performance. Monte Carlo models are better at figuring out risks because they look at how well a portfolio does in thousands of market situations. Using AI predictions and Monte Carlo stress tests, portfolio managers can make firm, adaptable plans to improve long-term success and resist market shocks. National wealth funds, pension funds, and endowments use MPT-based static asset allocation models. However, AI and Genetic Algorithm models are better at predicting returns and instability than static methods. Institutional investors can practice for financial crises and economic shocks with Monte Carlo stress tests. This makes their plans to protect their cash better. Asset allocation and Monte Carlo risk models that AI runs can help big investors grow their money over the long term and lower systemic risk. To minimize black-box decision-making risks, regulators must ensure that AI-driven financial models are open, trustworthy, and easy to understand. Regulatory frameworks should include Monte Carlo simulations and scenario-based stress testing to determine how vulnerable the economic system is in the worst-case situation. These findings highlight the need for portfolio managers to consider investor sentiment shifts, particularly the increasing role of green investors in shaping global investment trends.

Limitations

AI-driven optimization models and Genetic Algorithms outperform traditional financial models, yet specific problems exist. Most restrictions stem from skewed data, Monte Carlo simulation assumptions, and computing issues. AI-based portfolio optimization relies on historical financial data, which may not predict market behaviour. AI models trained on financial data before 2020 may be unable to foresee new crises like the COVID-19 market meltdown, the Russia-Ukraine war, or unexpected monetary policy shifts. Traditional AI-based portfolio hedging algorithms think stocks and bonds have a negative correlation, meaning bonds rise when markets fall.

Other issues include Monte Carlo's assumption that returns are normally distributed, which ignores “black swan” market events. While Monte Carlo models predict a log-normal distribution, financial markets often have fat-tailed distributions. Crashes and excessive volatility occur more often than Monte Carlo models predict. Because they are based on normal distribution, Future portfolio optimization frameworks should include fat-tailed distributions and dynamic correlation models. Stress tests and risk assessments are more accurate since these models change asset correlations as market conditions change. AI and Genetic Algorithm models require a lot of processing power, making them difficult for individual purchasers and smaller financial organizations to deploy. Traditional portfolio models don't require much computer power, but AI-driven approaches require deep learning infrastructure, high-frequency data processing, and large-scale cloud computing. Cloud-based AI portfolio optimization solutions could make financial products with APIs more manageable.

Directions for Future Research

Traditional portfolio optimization focuses on stocks, bonds, and commodities. However, modern investment techniques increasingly involve cryptocurrency, ESG investments, real estate, and private equity. New optimization algorithms are needed to diversify portfolios for these assets due to their risk-return profiles. AI models that analyze and include these assets will help diversify portfolios and boost long-term risk-adjusted returns. Future research on hybrid AI-Monte Carlo portfolio management frameworks seems promising. Monte Carlo simulations are good at testing and judging risk, and AI models are good at determining how much something will be worth. Alternatively, these steps are often used separately. Researchers should use AI's ability to see into the future and Monte Carlo's ability to model risk together to make a financial system that can change independently. This mixed method allows portfolios to react quickly to market changes using real-time data to keep risk predictions current. Also, it would be helpful to investigate how reinforcement learning can be used for adaptive real-time stock rebalancing. With markets that change quickly, rebalancing a stock once a year or every three months might not work anymore. It is called reinforcement learning, which is when AI learns from interactions. As a result, financial plans might be able to learn independently and adjust to market changes without any external help. Building AI rebalancing systems that can handle volatile markets independently could help investors stabilize their investments.

Conclusion

This study underscores the effectiveness of quantitative financial modelling in managing investment portfolios under uncertain and volatile market conditions. The findings demonstrate that AI-driven models and evolutionary algorithms significantly outperform traditional approaches in optimizing risk-adjusted returns by comparing Traditional Modern Portfolio Theory (MPT), Monte Carlo Simulations, AI-Based Optimization, and Genetic Algorithms. Monte Carlo simulations enhance risk assessment and stress-testing capabilities, providing a more comprehensive framework for evaluating portfolio vulnerabilities. Sustainable investment techniques are becoming increasingly important, according to the study's findings. This is especially true for green investors, who want high-performance portfolios that have little environmental impact.

As the financial landscape evolves, AI-driven models can be refined to incorporate ESG metrics, ensuring enhanced decision-making capabilities for green investors in dynamic markets. AI and Genetic Algorithms excel in dynamic asset allocation, allowing portfolios to adjust and ensuring resilience even during extreme market volatility. Monte Carlo simulations estimate portfolio risk better than MPT models because they capture downside hazards better. Traditional finance assumes stable markets and established risk-return relationships. Monte Carlo methods provide scenario-based risk modelling, which prepares investors for unexpected market disruptions. Due to real-time market, economic, and volatility fluctuations, AI-based portfolio optimization makes investments more adaptable. Because they cannot learn or adapt to real-world conditions, static allocation models do not operate as well as AI-driven methods.

The results suggest that portfolio managers utilize hybrid AI-Monte Carlo models, integrating AI's predictive analytics with Monte Carlo's rigorous risk assessment. This blended technique actively manages risks and optimizes returns in unstable settings. AI-driven methods that respond to economic developments should replace MPT-based asset allocations for institutional investors like pension funds and foundations. Cloud-based AI portfolio management tools simplify machine learning-driven asset allocation strategies for regular investors. These tools offer individualized portfolio rebalancing to ensure the optimal asset mix for risk tolerance and market conditions.

The study confirms that AI and Genetic Algorithms significantly enhance risk-adjusted returns, making them valuable tools for green investors seeking sustainable, high-performance investment portfolios. Integrating green bonds into portfolio management strategies provides investors with an additional hedge against systemic risks while supporting sustainable economic development. Green bonds' relatively lower volatility and resilience to financial shocks make them suitable for long-term diversification, particularly in uncertain market conditions. Future research should explore hybrid AI-ESG portfolio models that leverage green finance instruments to optimize financial performance and sustainability goals.

Policymakers should establish AI regulatory frameworks to monitor algorithmic financial models. AI-powered quantitative finance solutions may improve as the financial markets get more complicated and more challenging to predict. There will be an increase in machine learning, portfolio rebalancing based on reinforcement learning, and alternative asset modelling when making investment choices. Private equity, bitcoin, and ESG-based investments need new ways to optimize, considering non-traditional risk factors and making better plans for diversification. Quantum computing and big data analytics will help financial models by speeding up calculations and improving risk-adjusted portfolio optimization. AI models will keep learning, letting them predict the market and rebalance themselves automatically without any help from a person. Automated trade might be able to adapt to changes in the market with reinforcement learning. This would help stock management adjust better to changes in the economy.

Credit Authorship Contribution Statement

Ruslan Boiko: conceptualization; methodology; writing – original draft; supervision. Daria Butenko: formal analysis; data curation; visualization; writing – review & editing. Andrii Frolov: investigation; validation; resources; project administration. Andrii Moisiiakha: software; data curation; methodology; writing – review & editing. Viktoriia Rudevska: literature review; visualization; writing – original draft. All authors have read and agreed to the final version of the manuscript.

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Not applicable.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data that support the findings of this study were obtained from Bloomberg Terminal, Yahoo Finance, Federal Reserve Economic Data (FRED), and World Bank databases. These data are publicly available at https://www.bloomberg.com, https://finance.yahoo.com, https://fred.stlouisfed.org, and https://data.worldbank.org. The processed datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

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