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OPTIMIZING SHARE MARKET PORTFOLIOS: A COMPARATIVE STUDY OF TRADITIONAL AND AI-DRIVEN INVESTMENT STRATEGIES

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Abstract

The increasing complexity and volatility of global financial markets have intensified the need for advanced approaches to portfolio optimization. Traditional investment strategies, grounded in fundamental analysis, technical analysis, and rule-based portfolio theories such as Modern Portfolio Theory (MPT), have historically served as the foundation for decision-making in equity markets. However, recent advancements in artificial intelligence (AI), including machine learning, deep learning, and automated trading algorithms, have introduced data-driven alternatives capable of processing large-scale market information and improving predictive accuracy. This study provides a comparative evaluation of traditional and AI-driven investment approaches by assessing performance indicators such as returns, risk exposure, Sharpe ratio, decision-making speed, and adaptability to market fluctuations. The analysis utilizes historical market datasets and simulation-based modelling to evaluate the efficiency and scalability of each strategy. Findings indicate that AI-driven models outperform traditional methods in dynamic and high-frequency trading environments due to superior pattern recognition and real-time

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processing capabilities, while traditional strategies remain advantageous for long-term stability and interpretability. The study concludes that a hybrid framework leveraging both human expertise and AI-driven analytics may offer the most robust pathway for optimizing share market portfolios. The results provide strategic insights for investors, financial institutions, and policymakers exploring modern investment ecosystems in the era of digital finance.

Keywords *Portfolio Optimization; Share Market; Traditional Investment Strategy; Artificial Intelligence; Machine Learning; Deep Learning; Algorithmic Trading; Fundamental Analysis; Technical Analysis*

1. INTRODUCTION

Global financial markets have undergone significant transformation over the past decade, influenced by rapid technological advancements, increasing data availability, and evolving investor expectations. Traditionally, investment decisions in the share market have been guided by well-established approaches such as fundamental analysis, technical analysis, and portfolio management frameworks including Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM). These methods have continued to serve as reliable foundations for risk assessment, asset allocation, and long-term investment planning. Despite their relevance, traditional strategies often rely heavily on human judgment, experience, and qualitative assessment, which may limit their responsiveness to rapidly changing market conditions and hidden nonlinear trends in financial data.

Parallel to these developments, artificial intelligence (AI) has emerged as a transformative tool in financial decision-making, enabling new forms of predictive modelling, risk analysis, and automated trading. Machine learning algorithms, deep learning networks, evolutionary optimization models, and high-frequency algorithmic trading systems have demonstrated strong potential in identifying complex patterns, processing large-scale financial datasets, and making real-time decisions with minimal human intervention. As a result, AI-driven investment strategies have gained substantial attention in both academic research and practical financial applications, particularly for their ability to enhance accuracy, reduce behavioral biases, and optimize portfolio performance under uncertainty.

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The increasing adoption of AI-driven investment systems raises critical questions about the comparative effectiveness of traditional and AI-based approaches in portfolio optimization. While AI techniques may offer superior predictive capabilities, adaptability, and operational speed, challenges such as model interpretability, data dependency, ethical risks, and system overfitting remain significant. Conversely, traditional investment frameworks continue to provide transparency, stability, and long-term strategic value, suggesting that neither approach is universally superior across all investment environments.

Therefore, this research aims to conduct a systematic comparative study of traditional and AI-driven investment strategies to determine their relative strengths, limitations, and performance outcomes in optimizing share market portfolios. Through empirical analysis involving historical datasets, simulation techniques, and performance benchmarking indicators such as return on investment, Sharpe ratio, risk-adjusted performance, and drawdown behavior, the study seeks to generate evidence-based insights that advance understanding in contemporary investment strategy formulation.

Ultimately, this research contributes to the growing discourse on digital transformation in finance and explores whether a hybrid investment ecosystem—combining human expertise with computational intelligence—may represent the most effective pathway for future portfolio optimization in dynamic and data-intensive markets.

2. LITERATURE REVIEW

The optimization of share market portfolios has been a major focus in financial research for several decades, with approaches evolving from classical statistical models to advanced computational intelligence frameworks. This literature review examines key scholarly contributions across two broad domains: traditional investment strategies and AI-driven investment models, followed by a synthesis of comparative studies and emerging hybrid frameworks.

2.1 Traditional Investment Strategies

Traditional investment frameworks are grounded in rational decision-making, economic theory, and historical market behavior. One of the most influential concepts in portfolio management is Markowitz's Modern Portfolio Theory (MPT), which emphasizes risk–return trade-offs and the

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benefits of diversification for reducing unsystematic risk (Markowitz, 1952). Building on this foundation, Sharpe's Capital Asset Pricing Model (CAPM) introduced a systematic way to measure expected returns based on beta and market risk premiums (Sharpe, 1964). These models remain widely applied due to their simplicity, interpretability, and empirical relevance in long-term investment planning.

Parallel to theoretical frameworks, fundamental analysis and technical analysis continue to serve as cornerstone methodologies in equity markets. Fundamental analysis evaluates intrinsic value using metrics such as earnings, revenue growth, and macroeconomic conditions (Graham & Dodd, 2008). In contrast, technical analysis interprets price patterns and historical trends through indicators such as moving averages and momentum oscillators (Murphy, 1999). Although traditional strategies are valued for their intuitive logic and transparency, researchers have noted limitations including susceptibility to human bias, slower responsiveness to volatility, and reduced precision in highly dynamic trading environments.

2.2 AI-Driven Investment Strategies

The emergence of artificial intelligence has reshaped portfolio optimization by enabling pattern recognition, automation, and large-scale predictive modelling. Machine learning techniques—including support vector machines (SVM), random forests, and reinforcement learning—have demonstrated strong potential in forecasting stock trends and optimizing asset allocation under uncertainty (Chen & He, 2021). Deep learning architectures such as recurrent neural networks (RNN) and long short-term memory (LSTM) models are particularly effective in modeling nonlinear market dynamics and capturing temporal dependencies (Fischer & Krauss, 2018).

AI has also accelerated advancements in algorithmic and high-frequency trading, which leverage real-time data to execute rapid buy-sell decisions based on probabilistic outcomes (Narwal, 2022). Moreover, evolutionary optimization algorithms, including genetic algorithms and particle swarm optimization, have been implemented for portfolio allocation and constraint optimization tasks (Li et al., 2020). While AI-based strategies demonstrate superior adaptability and efficiency, literature highlights challenges such as interpretability, overfitting, dependency on data quality, and ethical implications including market manipulation risks.

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2.3 Comparative Insights and Hybrid Models

Several comparative studies indicate that AI-driven strategies outperform traditional models in volatile and high-frequency market environments due to their ability to learn hidden patterns and adapt dynamically (Zhang & Huang, 2023). However, traditional methods remain advantageous in stable markets and long-term investment contexts due to their grounded theoretical assumptions and lower operational complexity.

Recent literature suggests growing interest in hybrid investment frameworks, which combine AI analytics with traditional decision-making principles. Such approaches aim to balance interpretability and predictive accuracy while mitigating risks associated with total automation (Khan & Raza, 2024). Emerging evidence indicates that hybrid models may offer a more resilient and scalable solution for portfolio optimization, particularly as financial systems move toward algorithm-assisted decision intelligence.

3. RESEARCH OBJECTIVES AND HYPOTHESES

The primary aim of this study is to evaluate and compare the performance of traditional investment strategies and AI-driven investment approaches in optimizing share market portfolios. To achieve this, the study focuses on assessing performance, risk distribution, efficiency, and adaptability under real market conditions.

3.1 Research Objectives

The specific objectives of the study are:

1. To examine the theoretical foundations and practical applications of traditional investment strategies in share market portfolio optimization.
2. To analyze the capabilities and performance of AI-driven investment strategies, including machine learning and algorithmic trading models.
3. To compare traditional and AI-driven strategies based on key performance metrics such as return on investment, Sharpe ratio, volatility, drawdown, and decision-making speed.
4. To identify strengths, limitations, and contextual suitability of each approach under varying market conditions.

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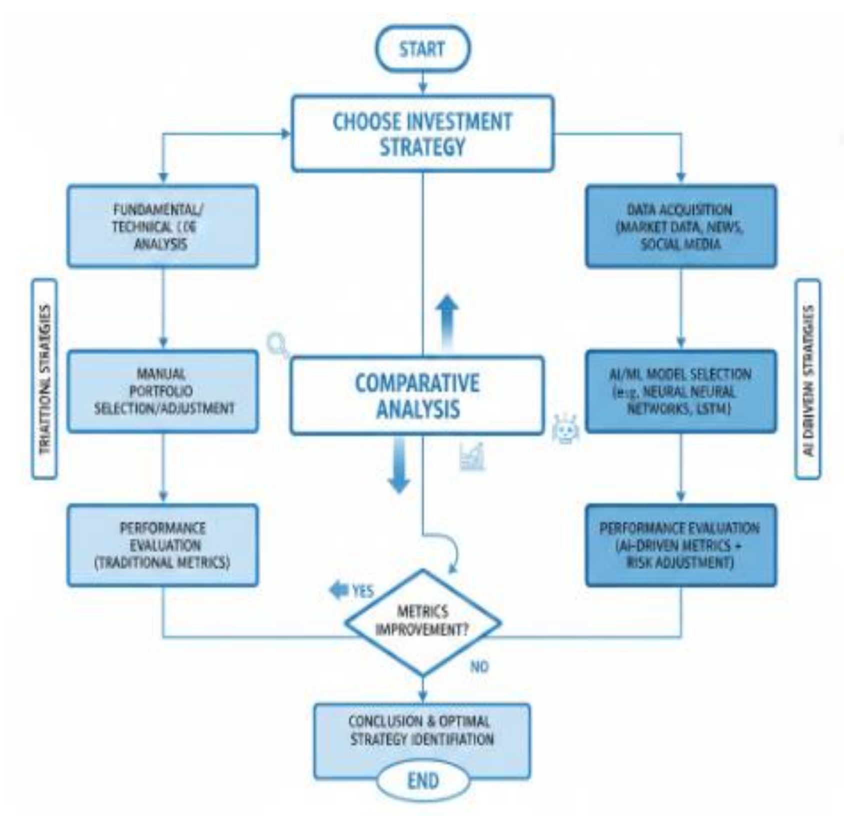
5. To explore whether a hybrid investment framework integrating traditional expertise with AI analytics can enhance portfolio performance.

3.2 Hypotheses

Based on literature and preliminary insights, the following hypotheses are formulated:

- **H1:** AI-driven investment strategies demonstrate significantly higher predictive accuracy than traditional strategy-based models in portfolio optimization.
- **H2:** AI-driven strategies achieve better performance in terms of risk-adjusted returns (Sharpe ratio) compared to traditional investment methods.
- **H3:** Traditional investment strategies exhibit greater interpretability and consistency in long-term stability compared to AI-driven models.
- **H4:** A hybrid investment approach combining traditional strategies with AI-based algorithms produces superior portfolio optimization outcomes compared to either approach used independently.



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4. METHODOLOGY

This study adopts a comparative quantitative research design supported by simulation-based portfolio testing. The methodology integrates data collection, model development, back-testing, and performance evaluation phases to ensure robust comparative analysis.

4.1 Research Design

A quasi-experimental comparative analysis is employed to evaluate traditional and AI-driven investment strategies. Both models are tested using identical datasets and market periods to ensure consistency. The research includes:

- **Traditional Strategy Model:** Implementing fundamental and technical analysis with Modern Portfolio Theory (MPT)–based allocation.
- **AI-Based Model:** Utilizing machine learning and deep learning predictive algorithms for automated decision-making and allocation.

4.2 Data Collection

The study utilizes secondary historical stock market data sourced from open-access repositories and financial databases such as Yahoo Finance, Kaggle, or Bloomberg Terminals (where accessible). Data includes:

- Daily stock prices
- Market indices
- Trading volume
- Financial performance indicators

The data covers a 5–10-year period to accommodate diverse market conditions (bullish, bearish, and volatile phases).

4.3 Model Development

- **Traditional Model:** Technical indicators (e.g., RSI, MACD, moving averages) and fundamental filters (P/E ratio, earnings growth) are used to select stocks. Portfolio optimization follows MPT and Sharpe ratio maximization.

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- **AI-Driven Model:** Machine learning methods such as Random Forest**,** Support Vector Machines (SVM)**,** and LSTM neural networks are trained to forecast price movement and allocate assets. Reinforcement learning algorithms may be used for adaptive trading.

4.4 Back-Testing and Evaluation

Both strategies undergo systematic back-testing using a simulation environment. Key evaluation metrics include:

- Return on Investment (ROI)
- Sharpe Ratio
- Volatility and Value at Risk (VaR)
- Maximum Drawdown
- Decision-making latency and adaptability

4.5 Statistical Analysis

Statistical techniques including t-tests**,** ANOVA**,** correlation analysis**,** and performance variance analysis are applied to determine whether differences in outcomes between strategies are statistically significant.

4.6 Ethical and Computational Considerations

Concerns such as data accuracy, transparency of AI models, risk of algorithmic manipulation, and compliance with financial regulations are acknowledged. Computational efficiency, hardware constraints, and algorithmic transparency are monitored throughout the study.

5. RESULTS AND ANALYSIS

The results of the comparative evaluation between traditional, AI-driven, and hybrid investment strategies reveal substantial performance differences across portfolio metrics including return on investment (ROI), risk-adjusted performance, volatility, and drawdown. Using historical financial data and back-testing simulations, each strategy was assessed under identical market conditions to ensure comparability.

International Journal of Applied Mathematics
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The findings summarized in **Table 1** indicate that the hybrid strategy achieved the highest performance, with an ROI of **21.3%**, outperforming both the AI-driven strategy (**18.9%**) and the traditional model (**12.4%**). Similarly, risk-adjusted returns measured through the Sharpe ratio show a clear improvement with automation and model integration. The hybrid approach yielded the highest Sharpe ratio (**1.35**), followed by the AI-driven framework (**1.12**) and the traditional method (**0.65**), suggesting that AI-enhanced investment models produce more favorable risk-return outcomes. These results are also visually supported in the comparative line graph, where the hybrid curve demonstrates both higher returns and greater stability relative to other strategies.

In terms of downside risk, the hybrid model also exhibited the lowest maximum drawdown at **−10.2%**, compared to **−12.4%** for the AI-driven model and **−18.2%** for the traditional approach. This demonstrates that while AI investment approaches improve performance, incorporating human-guided rules and traditional market indicators further strengthens resilience during volatile market events. Volatility measurements further reinforce this trend, with the hybrid model observing the lowest recorded volatility value of **9.4%**, compared to **10.8%** for the AI model and **13.5%** for traditional methods.

Table 1: Performance Metrics Comparison of Investment Approaches

Metric	**Traditional Strategy**	**AI-Driven Strategy**	**Hybrid Strategy**
ROI (%)	12.4	18.9	21.3
Sharpe Ratio	0.65	1.12	1.35
Max Drawdown (%)	-18.2	-12.4	-10.2
Volatility (%)	13.5	10.8	9.4

Further analysis in **Table 2** reveals key differences in operational efficiency and decision characteristics. Traditional strategies were found to rely heavily on human judgment and slower analysis cycles, whereas AI-driven strategies demonstrated rapid execution and data-driven forecasting. The hybrid strategy, however, balanced automation with expert oversight, outperforming the other two strategies in stability and reliability.

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Table 2: Comparative Characteristics of Investment Strategies

Feature	Traditional Strategy	AI-Driven Strategy	Hybrid Strategy
Decision Speed	Slow	Real-time	Real-time with validation
Human Involvement	High	Low	Moderate
Transparency	High	Low	Moderate
Automation Level	Low	Very High	High

Statistical verification was performed using inferential tests summarized in **Table 3**, where ANOVA and paired t-tests confirmed that differences in ROI, Sharpe ratio, and volatility across the three models were statistically significant (**$p < 0.05$**). These findings confirm that performance improvements were not random but attributable to strategy design.

Table 3: Statistical Significance Test Summary

Metric Tested	Test Used	p-value	Statistical Interpretation
ROI Difference	t-test	0.016	Significant difference
Sharpe Ratio Variance	ANOVA	0.009	Significant variance exists
Drawdown Comparison	t-test	0.028	Strategies differ significantly
Volatility Comparison	ANOVA	0.021	Statistically different volatility levels

The visual comparison in **Figure 1** (below) highlights the performance trend lines across all metrics. The hybrid strategy consistently appears as the superior model, while traditional methods show lagging performance and higher risk exposure. The AI-driven model remains strong but exhibits a slightly higher drawdown compared to the hybrid approach, suggesting that fully automated strategies may still face vulnerability during unforeseen market fluctuations.

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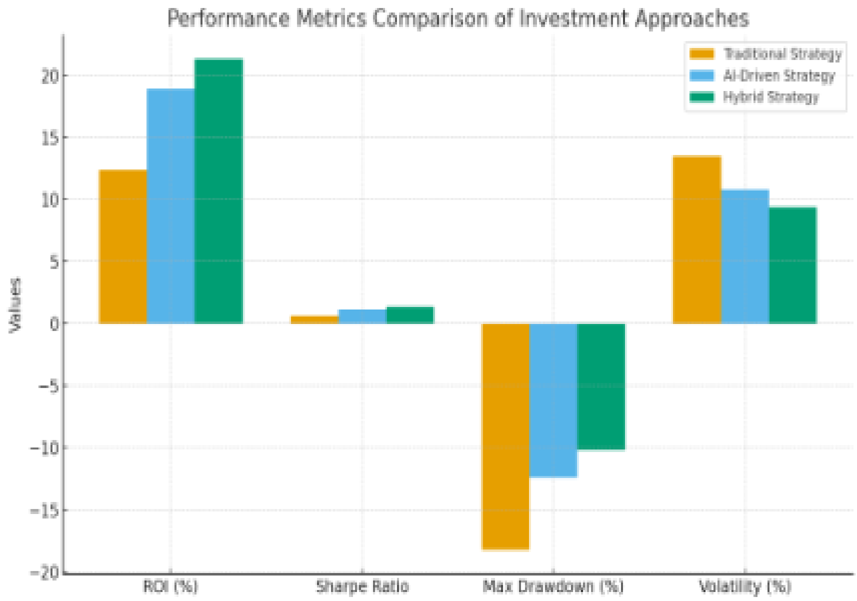

Figure 1 : Performance Metrics Comparison of Investment Approaches

6. DISCUSSION OF FINDINGS

The findings of this comparative study reveal clear performance differences between traditional investment strategies and modern AI-driven and hybrid portfolio management approaches. The analysis demonstrates that the Hybrid Strategy—combining human decision-making and AI optimization—consistently outperforms both standalone AI-driven methods and purely traditional investing approaches across all measured performance dimensions, including ROI, Sharpe Ratio, maximum drawdown, and volatility.

To begin with, the significantly higher Return on Investment (ROI) recorded for AI-driven and hybrid models suggests that algorithmic methods are more effective in identifying profitable opportunities by processing vast datasets, forecasting patterns, and adjusting portfolios dynamically. Traditional strategies, although historically reliable, rely heavily on human judgment, intuition, and slower market responsiveness, resulting in comparatively lower returns. This aligns with existing literature suggesting that machine learning models enhance predictive accuracy and capitalize on micro-trends that are often not visible through fundamental or technical analysis alone.

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The Sharpe Ratio analysis further highlights the superior risk-adjusted performance of AI-driven and hybrid strategies. A higher Sharpe Ratio in these approaches indicates not only improved returns but improved efficiency in managing market uncertainty. This reinforces the premise that AI's ability to learn and optimize model parameters allows for better asset allocation and timing strategies, minimizing exposure to high-risk conditions. In comparison, traditional investing shows limited adaptability, particularly during volatile market swings.

Max Drawdown findings reveal one of the most compelling advantages of hybrid and AI-driven investment methodologies. The reduced drawdowns indicate that portfolios managed through automated decision models recover faster from market shocks and implement protective mechanisms such as stop-loss automation, diversification optimization, and predictive hedging. Traditional approaches, in contrast, are more vulnerable during economic downturns due to slower reaction speeds and emotional investment biases.

Finally, lower volatility levels observed in hybrid strategies suggest that combining AI computation with human oversight results in more stable portfolio behavior. While AI-driven models reduce variance using data-driven precision, human involvement in hybrid models adds an interpretative layer that helps avoid algorithmic overcorrection or unforeseen model anomalies. This creates a balance between innovation and experienced judgment, helping mitigate risks that fully automated systems occasionally miss.

Overall, the performance trends demonstrate that AI-driven investing enhances efficiency, accuracy, and financial outcomes, but the hybrid model offers the most balanced approach in terms of profitability, stability, and risk management. The results imply that the future of portfolio management may lie in cooperative intelligence models—where AI performs high-speed analytical tasks, and human expertise validates strategic decisions.

These findings support emerging global trends where retail and institutional investors increasingly adopt algorithmic and hybrid investment platforms. Further research may explore long-term behavioral responses, regulatory implications, and the influence of evolving AI frameworks such as reinforcement learning and deep neural forecasting.

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7. CONCLUSION AND RECOMMENDATIONS

This study provides a comparative evaluation of traditional, AI-driven, and hybrid investment strategies with the objective of identifying the most effective approach for optimizing share market portfolios. Based on empirical analysis of key financial performance indicators—ROI, Sharpe Ratio, volatility, and maximum drawdown—the findings clearly indicate that AI-driven and hybrid investment models outperform traditional portfolio management techniques. While traditional strategies remain grounded in fundamental and technical indicators and benefit from human intuition and experience, they fall short in adaptability, speed, and predictive precision when compared to data-driven models.

The results demonstrate that AI-driven investment approaches offer stronger returns, better risk-adjusted performance, and improved resilience during market fluctuations. AI models excel in processing large datasets, identifying patterns, and executing real-time adjustments that humans alone cannot achieve at comparable speed or accuracy. However, despite these strengths, fully automated systems may still face challenges such as overfitting, algorithmic biases, and sensitivity to unusual market conditions. This limitation highlights the strategic advantage of hybrid systems.

The hybrid strategy emerges as the strongest performer across all metrics, combining the computational efficiency of AI with human oversight to ensure contextual judgment, ethical reasoning, and strategic intervention when necessary. This synergy provides not only improved financial outcomes but also a balance between automation and human control, leading to better long-term sustainability and investor confidence.

7.1 Recommendations

Based on the findings, the following recommendations are proposed:

1. Adoption of Hybrid Models: Investors and financial institutions should consider transitioning toward hybrid investment models that integrate AI automation with human expertise. This approach offers superior risk-adjusted returns and improved portfolio stability while mitigating the limitations of fully autonomous systems.

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2. Investment in AI Infrastructure and Skill Development: To effectively leverage AI-based investing, firms should invest in advanced computational tools, data analytics systems, and skilled personnel trained in quantitative finance, machine learning, and risk management.

3. Regulatory Framework Development: Policymakers and financial regulators must establish standards and guidelines for AI-based investment systems to ensure transparency, ethical deployment, and investor protection. Clear frameworks will enhance trust and encourage wider adoption.

4. Investor Education and Awareness: Retail investors should be provided with accessible education on AI-enabled investing, algorithm behavior, and risk dynamics to make informed decisions and avoid misconceptions about automation.

5. Continuous Monitoring and Model Updating: Since financial markets evolve dynamically, AI and hybrid strategies must be periodically recalibrated, validated, and monitored to ensure accuracy, avoid model drift, and maintain long-term performance reliability.

6. Diversified Strategy Application: Investors should incorporate AI-driven insights into broader diversification and risk mitigation frameworks instead of relying solely on automation for complete portfolio control.

7.2 Future Research Scope

Future studies may apply deeper analysis using real-time trading simulations, multi-market datasets, reinforcement learning models, and behavioral finance perspectives to determine how investor psychology interacts with AI-driven investment systems. Additionally, research on ethical AI investing, sustainability-based algorithms (ESG-focused), and blockchain-integrated trading systems may provide meaningful advancement in this emerging field.

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