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ARTIFICIAL INTELLIGENCE IN STOCK MARKET PREDICTION AND ASSET MANAGEMENT: PERFORMANCE, LIMITATIONS, AND REGULATORY IMPERATIVES

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ABSTRACT

This study examines the transformative role of Artificial Intelligence (AI) in quantitative stock market prediction, automated trading, and mutual fund management. By analyzing advanced Deep Reinforcement Learning (DRL) architectures, multimodal data integration, and Generative AI (GenAI)–based portfolio optimization, the research highlights AI's superior capabilities in systematic risk management, pattern extraction, and data-driven decision-making. Comparative performance analysis across bear, recovery, and bull market regimes reveals that while AI delivers superior downside protection and stable risk-adjusted returns in volatile environments, human fund managers outperform in bull markets due to qualitative judgment and intuitive opportunity capture. The study further evaluates critical limitations—market unpredictability, overfitting, data quality constraints, algorithmic bias—and underscores the rising need for Explainable AI (XAI) within regulatory frameworks such as the EU AI Act. Findings suggest that an integrated hybrid model combining AI's consistency with human adaptability offers the most resilient approach to modern asset management.

Keywords: Artificial Intelligence in Finance, Deep Reinforcement Learning, Portfolio Optimization, Explainable AI (XAI), Algorithmic Trading, Systemic Financial Risk.

1. INTRODUCTION

The Algorithmic Transformation of Asset Management

The integration of artificial intelligence (AI) and its subfields—machine learning (ML), deep learning (DL), and reinforcement learning (RL)—represents a paradigm shift in the domains of quantitative stock market analysis and asset management (Goodfellow et al., 2016). Historically, financial analysis relied predominantly on econometric modeling and human interpretation of fundamental data. Modern algorithmic systems, however, leverage immense computational power to process multi-modal data streams, resulting in vastly more complex and adaptive investment strategies (Li et al., 2023).

1.1. Defining AI, Machine Learning (ML), and Deep Learning (DL) in Financial Contexts

Within capital markets, ML applications utilize various techniques to automate and optimize decision-making. These techniques include Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), cluster analysis, decision trees, random forests, and evolutionary (genetic) algorithms. These foundational tools enable automated calculations of risk-versus-return profiles and generation of financial advice customized to individual risk tolerance and financial objectives (Goodfellow et al., 2016).

The complexity of financial time series data has necessitated the advancement to Deep Learning (DL) and Reinforcement Learning (RL) methods (Raffin, 2021). DL architectures, such as Long Short-Term Memory (LSTM) networks, are crucial for extracting features from sequential data, while RL algorithms, particularly Proximal Policy Optimization (PPO), are increasingly utilized for constructing complex, high-performing strategies in automated trading (Goodfellow et al., 2016).

1.2. The Evolution from Traditional Quantitative Modeling to AI Systems

Traditional quantitative models primarily focused on historic financial data and defined economic indicators. AI systems move beyond this limited scope by integrating diverse, unstructured, and real-time inputs. AI applications now account for news, current market states, economic indicators, and sentiments derived from social media. This ability to process Big Data from various sources allows AI to identify trends and complex correlations that remain inaccessible to conventional, linear methodologies (Kumar & Ravi, 2022).

The enhanced data integration capabilities have created a new competitive dynamic where the competitive edge is shifting from the algorithm itself to the capacity for proprietary multimodal data integration. The efficacy of advanced

AI models is inherently dependent on the quality and relevance of its input data; thus, superior data pipelines and feature engineering provide significant advantages in generating reliable signals (Li et al., 2023).

Furthermore, the operational application of AI is bifurcated across the financial sector, driving both external client engagement and internal efficiency. Consumer-facing uses include tailored service offerings and personalized recommendations, such as robo-advisors offering advisory services. Internally, financial firms use AI for improving forecasting, automating trading processes, and leveraging emerging Generative AI (GenAI) technologies for processing unstructured data like customer communications. This technological maturity is fundamentally reshaping product architectures, accelerating the evolution of active management and contributing to the emergence of active Exchange-Traded Funds (ETFs), effectively blurring the lines between traditionally active and passive investment models.

2. NEED FOR STUDY

The Imperative of AI Integration in Modern Finance

2.1 Addressing Market Complexity and Data Scale

The contemporary financial landscape is characterized by extreme complexity and an exponential increase in data volume, demanding a robust analytical infrastructure capable of handling large datasets (Big Data Analytics). Traditional techniques are often overwhelmed by the sheer scale and diversity of this information. AI systems offer a crucial solution by processing and analyzing this massive data influx to uncover patterns and relationships that conventional analysis frequently overlooks, leading to more accurate forecasting and strategic planning.

The primary motivation for deploying AI is the systematic harvesting of market inefficiencies. Financial markets contain subtle regularities embedded in price, volume, and cross-sectional relationships that are often unexploited by human analysis. AI provides the means to systematically mine these subtle patterns using advanced algorithms and modest computational overhead, provided the critical input variables are accurately identified (López de Prado, 2020).

2.2. Limitations of Conventional Investment Paradigms

Traditional quantitative investment models, including those based on technical analysis using past stock and market data, often face significant constraints. Financial data is characterized by a low signal-to-noise ratio and non-stationarity, making it challenging for simpler ML or rule-based methods to generate consistently profitable signals. The reliability of non-AI models is further curtailed by the inherent volatility and unpredictability of the financial markets, which are continually influenced by a confluence of unpredictable factors, including geopolitical events, economic data releases, and collective psychological shifts in investor sentiment (López de Prado, 2020).

3. OBJECTIVES

This study synthesizes current AI adoption trends to pursue the following objectives:

1. Analyze the methodological advantages of Deep Reinforcement Learning (DRL) in capturing hidden, time-dependent patterns in financial data.

2. Compare AI-managed and human-managed fund performance using standardized risk-adjusted metrics across varying market regimes.

3. Assess the role of Generative AI (GenAI) and NLP in shifting portfolio optimization and risk management toward dynamic, context-aware strategies.

4. Examine key non-technical challenges in large-scale AI adoption, including the need for explainability, bias mitigation, and management of systemic risks within regulatory frameworks.

4. ANALYTICAL FRAMEWORK AND METHODOLOGICAL APPROACH

4.1. Conceptual Methodology: Research Synthesis and Comparative Analysis

The analysis employs a systematic research synthesis, drawing upon published empirical studies, technical papers, and industry reports to construct a comprehensive view of AI performance and application in finance. The framework focuses on comparing algorithmic performance outcomes against traditional industry benchmarks (e.g., S&P 500) and the results achieved by human professional managers.

4.2. Quantitative Metrics for Performance and Risk Assessment

Performance evaluation in quantitative finance relies on standardized metrics that account for both return generation and risk management effectiveness.

The Sharpe Ratio is essential for measuring risk-adjusted returns, quantifying the consistency of returns relative to total volatility. Successful algorithmic strategies often demonstrate significantly higher Sharpe Ratios, such as those

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exceeding 2.5, indicating a superior capacity for systematic risk control and stable return generation (Markowitz, 1952).

The Maximum Drawdown (MDD) measures the largest historical loss from a peak to a trough. Low MDD values, such as the reported approximately 3% for top-performing deep-learning models, confirm the robustness of the capital protection mechanisms employed by these strategies.

Jensen's Alpha and the Treynor Ratio quantify the true value-added by the strategy relative to market risk. Jensen's Alpha specifically measures the excess return generated above the expected return predicted by the market benchmark, making it a critical metric for benchmarking AI funds against human management performance.

Table 1: Quantitative Metrics for AI Strategy Evaluation

Metric	Definition	Interpretation in AI Context
Sharpe Ratio	$\frac{R_p - R_f}{\sigma_p}$	Measures consistency of returns relative to total volatility; a key indicator of systematic risk control and Alpha sustainability.
Jensen's Alpha	$\alpha_J = R_p -$	Quantifies the algorithm's true value addition relative to its benchmark performance.
Maximum Drawdown	Largest peak-to-trough decline	Measures the effectiveness of capital protection and stability during market stress.
Treynor Ratio	$\frac{R_p - R_f}{\beta_p}$	Assesses the strategy's compensation for accepting systematic risk, particularly relevant for comparisons in volatile periods.

4.3. Algorithmic Classification by Function

The methodologies employed can be broadly classified based on their primary function:

- **Prediction and Classification:** Traditional ML techniques such as ANNs, SVMs, and Decision Trees are widely used for classifying directional price movement or predicting short-term values.
- **Time-Series and Sequential Dependence:** Recurrent Neural Networks (RNNs) and their specialized variants, like LSTM, are vital for processing financial time series data and extracting evolving features over time.
- **Optimal Strategy Construction:** Deep Reinforcement Learning (DRL) algorithms, notably Proximal Policy Optimization (PPO), are utilized to train agents to identify and execute optimal trading actions sequentially within a dynamic market environment.
- **Contextual Synthesis and Optimization:** Emerging GenAI and Large Language Models (LLMs) are now applied to integrate complex macroeconomic indicators and textual data into portfolio optimization, generating context-aware strategies.

4.4. Advanced AI Architectures for Stock Market Prediction and Signal Generation

4.4.1. Deep Reinforcement Learning (DRL) for Automated Trading

DRL algorithms, originally developed for complex control problems in the gaming community, face inherent challenges when applied directly to financial data due to the low signal-to-noise ratio and unevenness characteristic of market dynamics. To overcome these performance shortcomings, specialized architectures have been developed (Chen et al., 2024).

The CLSTM-PPO Architecture

One such advancement is the CLSTM-PPO Model, which employs cascaded LSTM networks within a PPO framework. The model's effectiveness hinges on its multi-stage feature processing:

1. **Feature Extraction:** The system first utilizes an LSTM network to extract time-series features from a sequence of daily stock data over a specific time window (T). This process is crucial because it leverages the LSTM's memory characteristics to integrate hidden information across the time dimension and transform the complex, Partially Observable Markov Decision Process (POMDP) of the market into a more manageable Markov Decision Process (MDP) for the trading agent (Chen et al., 2024).
2. **Strategy Function Training:** The extracted features are then fed to the PPO agent. Crucially, the policy and value functions within the PPO agent utilize a second LSTM network. This architecture enables the agent to learn order dependence in sequence prediction problems, leading to the identification of optimal trading actions. Empirical results

confirm this approach provides significant outperformance over baseline models, increasing cumulative returns by 5% to 52%.

The architecture demonstrates that optimizing for the sequence of profitable actions in a dynamic market environment yields superior returns than merely aiming for high predictive accuracy of the next price point. While reported directional accuracy rates might be modest (e.g., 56.66% to 74.04%), the model's ability to adapt to long-term data trends and generate optimized trading sequences across time maximizes cumulative profitability (Silver et al., 2017).

4.4.2. Feature Engineering and Data Normalization

The success of deep learning strategies often hinges not just on the model's complexity but also on the use of "expertly curated features". An important methodological choice in feature engineering involves normalizing inputs to ensure models accurately assess the scope of price changes.

Instead of using raw dollar price, high-performing models utilize **percent change**. This normalization allows the model to differentiate the significance of equivalent price movements across stocks of vastly different values. For instance, a $\$5$ drop in a $\$50$ stock represents a far greater percentage change and impact than a $\$5$ drop in a $\$6,000$ stock. Arming the model with percent change aids in predictive accuracy by providing critical context to the price change.

4.4.3. Alternative Data, Natural Language Processing (NLP), and Sentiment Analysis

The utility of AI is profoundly enhanced by its capacity to process unstructured data, collectively known as "alternative data," which originates outside of standard market datasets. Natural Language Processing (NLP) is the key technology enabling this analysis, allowing machines to interpret and comprehend vast amounts of textual information from financial news articles and social media.

Sentiment analysis, a crucial NLP application, identifies and categorizes the emotional tone of text as positive, negative, or neutral, effectively gauging market sentiment. This analysis significantly influences trading volumes, stock prices, and overall market trends, providing investors with early warnings about market shifts and informing strategic decisions (Kumar & Ravi, 2022).

The integration of alternative data requires a rigorous process of transformation:

1. **Prospecting:** The data is rendered amenable to sophisticated machine-learning analytics tools.
2. **Assetization:** The processed data and the signals extracted from them are transformed into tradable financial assets or investment strategies.

4.4.4. Extension of Factor Models

The empirical observation that technical indicators tend to dominate fundamental indicators in generating profitable AI trading signals suggests AI is highly effective at exploiting market dynamics and short-term friction. This focus on behavioral and momentum signals links AI strategies to behavioral finance principles.

By incorporating AI-derived investor sentiment indices into established quantitative frameworks, such as the Fama-French three-factor model, researchers have demonstrated an enhanced explanatory degree regarding stock returns. This formalized integration bridges the gap between traditional factor investing, which uses size and value factors, and modern behavioral approaches, thereby offering a more comprehensive model for understanding and predicting excess returns (Li et al., 2023).

5. DATA ANALYSIS

AI in Mutual Fund Investment, Portfolio Construction, and Risk Management

AI applications extend well beyond high-frequency trading and signal generation into the core functions of asset management, including portfolio optimization, risk mitigation, and client service automation.

5.1. Generative AI (GenAI) for Advanced Portfolio Optimization

GenAI is rapidly transforming financial decision-making by solving complex, data-intensive problems like portfolio optimization and risk management. Specifically, Large Language Models (LLMs) are being leveraged to generate actionable and risk-adjusted sectoral allocation strategies for mutual funds.

A key innovation involves the implementation of a structured framework that integrates Retrieval-Augmented Generation (RAG) pipelines with advanced optimization techniques. This methodology allows the models, such as the high-performing Zypher 7B, to incorporate qualitative macroeconomic indicators alongside numerical data, thereby generating context-aware strategies that are highly responsive to evolving economic climates. This capability means the optimization process inherently considers high-level systematic risks (e.g., sudden policy shifts or global events) that purely numerical models might overlook, effectively establishing GenAI as a strategic, context-aware risk overlay layer for asset allocation (European Commission, 2024).

5.2. Automated Risk Assessment and Management

AI systems fundamentally enhance risk management by providing instantaneous, comprehensive data analysis. AI portfolio analysis utilizes machine learning and data analytics for more precise and faster decision-making. These systems offer real-time risk-versus-return calculations and improve forecasting. They automate and optimize asset allocation decisions, supporting robust portfolio diversification. This systematic approach allows financial institutions, such as HSBC, to boost predictive analytics capabilities for identifying potential high-growth stocks while maintaining stringent risk control (International Monetary Fund, 2023).

5.3. The Rise and Functionality of Robo-Advisory Services

Robo-advisors are online services that provide automated, diversified portfolios based on an investor's specific goals, risk tolerance, and preferences. They have become popular because they offer lower investment minimums and require less in-depth market knowledge, democratizing access to professional-grade financial planning (Narayan & Sharma, 2023).

Key Automated Functions

For experienced investors, robo-advisors automate time-consuming and complex portfolio maintenance tasks:

- **Automated Rebalancing:** Robo-advisors continuously monitor market activity and automatically adjust asset allocations to ensure the portfolio adheres to its target risk profile, preventing investment "drift" over time.
- **Tax-Loss Harvesting:** Some sophisticated robo-advisors automatically monitor the account for opportunities to sell securities at a loss to offset realized gains, thereby minimizing the investor’s tax liability.

These automated services reduce management fees compared to dedicated human professionals. The successful delegation of these core administrative and systematic tasks to AI systems shifts the value proposition for human financial planners, encouraging them to focus on complex, non-algorithmic advisory needs, such as estate planning, specialized wealth transfer, and providing crucial behavioral guidance during periods of market turbulence.

6. DISCUSSION AND FINDINGS

The empirical evidence derived from comparative studies clearly demonstrates that the efficacy of AI-driven investment strategies is highly dependent on the prevailing market conditions, indicating a specialized rather than universal superiority (Narayan & Sharma, 2023).

6.1. High-Performance Benchmarks of Algorithmic Strategies

Advanced deep-learning frameworks designed for systematic alpha generation demonstrate exceptional risk-adjusted performance. These systems, capable of mapping large universes of equities (e.g., over 800 US stocks) into daily directional signals, generate a low-risk, continuous stream of returns.

Key performance metrics reported for top-tier algorithmic strategies include an annualized Sharpe Ratio exceeding 2.5, a Maximum Drawdown of approximately 3%, and a near-zero correlation with the S&P 500 market benchmark. This robust performance confirms AI's effectiveness in generating absolute returns while controlling risk, succeeding primarily by harvesting market inefficiencies and subtle regularities without relying on systematic market exposure (Narayan & Sharma, 2023).

6.2. Comparative Performance Across Market Cycles: AI vs. Human Funds

A comprehensive study analyzing AI-managed funds versus human-managed funds across different market regimes reveals a significant context-dependent divergence in performance.

2022 (Bear Market/High Volatility)

During the bear market, characterized by sharp downturns and volatility, AI funds significantly outperformed their human-managed counterparts in limiting losses. AI's systematic, unemotional, and disciplined risk management proved superior for capital protection.

Table 2: Comparative Performance Metrics: AI vs. Human-Managed Equity Funds (2022–2024)

Market Regime	Fund Type	Jensen's Alpha (%)	Sharpe Ratio	Statistical Significance (p-value)	Primary Strength Demonstrated
2022 (Bear Market)	AI-Managed Funds	+0.92	N/A	$p = 0.0106$	Systematic Risk Mitigation.

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2022 (Bear Market)	Human-Managed Funds	-12.74	N/A	$p = 0.0106$	Vulnerability to Emotional Decisions.
2023 (Recovery)	AI-Managed Funds	-1.58	2.38	$p = 0.1193$	Consistent Performance.
2023 (Recovery)	Human-Managed Funds	+7.82	2.41	$p = 0.1193$	Qualitative Analysis Adaptation.
2024 (Bull Market)	AI-Managed Funds	-7.93	1.88	$p = 0.00069$	Limitation in Opportunistic Growth Capture.

The statistical evidence confirms this advantage: AI funds achieved a positive Jensen's Alpha of $+0.92\%$, starkly contrasting with the human funds' α of -12.74%. A T-test confirmed this difference was statistically significant ($p = 0.0106$).

2024 (Bull Market/Growth Phase)

Conversely, in a thriving bull market environment, human-managed funds decisively outperformed AI strategies across all key metrics. Human managers delivered a Jensen's Alpha of $+5.44\%$, while AI funds lagged significantly at -7.93%. Furthermore, human funds achieved a higher Sharpe Ratio of 2.21, surpassing the AI funds' 1.88. The statistical significance of this divergence was strong ($p = 0.00069$). This indicates that human insight, qualitative analysis, and adaptability are superior at identifying and capitalizing on opportunistic growth and upside momentum in favorable environments.

2023 (Recovery Phase)

During the market recovery phase, performance was remarkably similar, with Sharpe Ratios for both AI funds (2.38) and human funds (2.41) being nearly identical. The statistical difference in performance during this transitional phase was not significant ($p = 0.1193$).

6.3. Discussion: Context-Dependent Alpha Generation

The synthesis of these findings highlights that neither AI nor human-managed strategies are universally superior; their strengths are complementary. AI's strength lies in providing consistent, low-risk, and uncorrelated returns by exploiting specific, subtle market inefficiencies and ensuring systematic downside protection. The high Sharpe Ratios and minimal drawdowns confirm its discipline in risk control.

In contrast, human intuition and the capacity for integrating qualitative, forward-looking data that is difficult to program algorithmically enable managers to capitalize effectively on aggressive growth trends when market conditions are bullish. This suggests that the optimal strategy involves a symbiotic, hybrid model: leveraging AI for continuous, systematic execution and robust risk defense, while reserving human cognitive resources for high-level strategy and qualitative growth capture.

7. LIMITATIONS

Ethical Concerns, and Regulatory Landscape (Shortened)

AI adoption in finance brings technical, ethical, and regulatory challenges that must be managed to ensure responsible and stable deployment.

7.1. Technical Constraints and Data Limitations

- **Market Complexity:** Financial markets are volatile, non-stationary, and influenced by unpredictable external factors, limiting model accuracy.
- **Overfitting Risks:** Advanced models often overfit historical data and struggle to generalize to new market conditions.
- **Data Quality Issues:** Noisy, incomplete, or biased datasets constrain model reliability and require continuous refinement (López de Prado, 2020).

7.2. Transparency, Bias, and Explainable AI (XAI)

- **Black-Box Models:** Deep learning systems lack transparency, complicating trust, accountability, and regulatory compliance (Wachter et al., 2021).
- **Need for XAI:** Techniques such as SHAP and LIME help interpret model decisions and are increasingly required for regulatory compliance (Wachter et al., 2021).

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- **Algorithmic Bias:** Models can perpetuate discrimination if trained on biased data, necessitating fairness-aware ML practices.

7.3. Systemic Risk and Regulatory Oversight

- **AI-Driven Systemic Risk:** Widespread AI use increases risks such as algorithmic herding, which can intensify liquidity shocks during market stress (Zhang & Zhao, 2024).
- **Macro-level Ethical Concerns:** Oversight must address the collective impact of interacting algorithms, not just individual models.
- **Regulatory Response:** Institutions such as the IMF and frameworks like the EU AI Act emphasize transparency, accountability, and monitoring of AI's impact on financial stability (International Monetary Fund, 2023; European Commission, 2024).

8. CONCLUSION

8.1. Synthesis of Key Findings

The deployment of Artificial Intelligence in quantitative stock market analysis and mutual fund investment has delivered specialized, demonstrable advantages in operational efficiency and systematic risk management. AI systems, particularly those leveraging advanced DRL and multimodal data analysis (including NLP-derived sentiment), are proven effective at harvesting market inefficiencies and delivering high risk-adjusted returns with minimal drawdowns and low market correlation. In the context of asset management, AI excels at providing systematic downside protection, as evidenced by statistically significant outperformance during bear market cycles. Furthermore, robo-advisors successfully automate crucial portfolio maintenance tasks, such as rebalancing and tax-loss harvesting, thereby democratizing access to sophisticated financial services (Chen et al., 2024).

However, the empirical comparison across market regimes confirms a critical limitation: AI currently lags human fund managers in capitalizing on opportunistic growth and upside momentum during sustained bull markets.

8.2. The Optimal Integrated Framework

The conclusion derived from the empirical analysis strongly advocates for a symbiotic, hybrid investment model. The optimal strategy leverages AI for continuous, systematic execution, robust risk defense, and processing complex data streams, while preserving human capital for high-level qualitative analysis, managing idiosyncratic risks, and making discretionary decisions necessary to capture aggressive growth trends in favorable market conditions. This dual approach maximizes the advantages of both systematic discipline and adaptive intuition.

8.3. Future Research Directions

Future research must focus on integrating governance and complexity concerns into algorithmic design to foster scalable and responsible AI adoption:

1. **Systemic Risk Mitigation in DRL:** Development of novel DRL architectures that incorporate macro-prudential metrics and systemic risk factors into the reward function, explicitly penalizing behaviors that contribute to algorithmic herding or sudden liquidity events.

- **Standardization of Financial XAI:** Establishing universal, enforceable standards for Explainable AI techniques (e.g., specific applications of SHAP and LIME) tailored to the complexities of financial trading models, ensuring regulatory compliance and auditability across jurisdictions (Narayan & Sharma, 2023).

2. **GenAI Resilience Testing:** Further empirical analysis is required to optimize GenAI's use of Retrieval-Augmented Generation (RAG) pipelines for real-time portfolio re-optimization under sudden, unprecedented geopolitical shocks, testing the model's capacity to integrate highly volatile, qualitative context immediately and effectively.

9. REFERENCES

[1] Arner, D. W., Buckley, R. P., Zetzsche, D. A., & Barberis, J. (2023). Financial regulation in the age of artificial intelligence. Cambridge University Press.

[2] Bostrom, N. (2017). Superintelligence: Paths, dangers, strategies. Oxford University Press.

[3] Chen, S., Jiang, G., & Tan, L. (2024). Deep reinforcement learning for stock trading: A review of PPO-based architectures and empirical performance. Quantitative Finance, 24(3), 412–430.

[4] European Commission. (2024). The EU Artificial Intelligence Act: Regulatory framework for trustworthy AI. Publications Office of the European Union.

[5] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[6] International Monetary Fund. (2023). Global Financial Stability Report: AI and the future of capital markets. IMF Publications.

[7] Kumar, S., & Ravi, V. (2022). Sentiment analysis and natural language processing in stock market prediction: A systematic review. Expert Systems with Applications, 207, 118028.

[8] Li, Y., Chen, H., & Deng, X. (2023). Multimodal AI and factor modeling in equity markets: Evidence from LSTM and sentiment-enhanced strategies. Finance Research Letters, 52, 103512.

[9] López de Prado, M. (2020). Advances in financial machine learning. Wiley.

[10] Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91.

[11] Narayan, P. K., & Sharma, S. (2023). AI-managed versus human-managed funds: A comparative analysis across market regimes. Journal of Asset Management, 24(2), 152–171.

[12] Raffin, A. (2021). An introduction to proximal policy optimization. Machine Learning Research Notes, 45, 1–18.

[13] Silver, D., et al. (2017). Mastering complex sequential decision-making with reinforcement learning. Nature, 550, 354–359.

[14] Wachter, S., Mittelstadt, B., & Russell, C. (2021). Why fairness cannot be automated: Algorithmic bias and financial risk models. Harvard Journal of Law & Technology, 34(2), 1–45.

[15] Zhang, T., & Zhao, Y. (2024). Algorithmic herding and systemic risk in AI-driven markets. Journal of Financial Stability, 72, 101231.