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A Survey on Multi Agent Framework for Asset Allocation and Portfolio Optimization

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Abstract: The rapid evolution of global financial markets, driven by increased data availability, market volatility, and the participation of diverse investors, has intensified the complexity of asset allocation and portfolio optimization. Traditional portfolio management techniques, while well established, rely on static assumptions and centralized decision-making, limiting their effectiveness in dynamic and non-stationary market environments. Recent advances in Artificial Intelligence (AI), particularly Reinforcement Learning (RL) and Multi-Agent Systems (MAS), have opened new avenues for adaptive, decentralized, and intelligent financial decision-making.

This review paper presents a systematic survey of Multi-Agent Artificial Intelligence frameworks for dynamic asset allocation and portfolio optimization. It synthesizes and analyzes recent research spanning multi-agent reinforcement learning, deep reinforcement learning, large language model (LLM)-based agents, and hybrid AI architectures applied to financial markets. The review examines agent cooperation and competition mechanisms, learning paradigms, reward formulations, and risk-aware optimization strategies employed across existing studies. Additionally, emerging trends such as hierarchical multi-agent learning, role-based agent specialization, and LLM-driven financial reasoning are discussed.

By critically evaluating the strengths, limitations, and practical challenges of current methodologies, this paper identifies key research gaps related to scalability, interpretability, transaction cost modeling, and real-time deployment. The survey aims to provide a comprehensive understanding of the current landscape of multi-agent AI in portfolio management and to serve as a foundation for future research toward robust, adaptive, and intelligent financial systems.

Keywords: Artificial Intelligence, Portfolio Optimization, Reinforcement Learning, Quantitative Finance, Risk Management, Dynamic Asset Allocation, FinTech.

I. INTRODUCTION

In recent years, financial markets have undergone significant transformation due to globalization, technological advancement, and the exponential growth of financial data. Investors and financial institutions face increasing pressure to make timely, accurate, and risk-aware decisions in highly volatile and uncertain environments. Asset allocation and portfolio optimization remain central to investment success, directly influencing returns, risk exposure, and long-term financial stability. However, the growing complexity of financial instruments, rapid market fluctuations, and interconnected global events have rendered traditional portfolio management approaches increasingly insufficient.

Conventional portfolio optimization techniques, such as mean-variance optimization and rule-based rebalancing strategies, are built on simplifying assumptions including market efficiency, static correlations, and normally distributed returns. While these methods have been widely adopted, they struggle to adapt to non-linear market dynamics and abrupt regime changes. Moreover, portfolio decisions driven by human expertise are often influenced by cognitive biases, emotional reactions, and limited information-processing capacity, which may result in suboptimal investment outcomes.

The integration of Artificial Intelligence (AI) into financial systems has introduced a paradigm shift in investment analysis and portfolio management. Machine learning and deep learning techniques have demonstrated strong capabilities in modeling complex financial patterns, predicting asset returns, and supporting automated trading strategies. More recently, Reinforcement Learning (RL) has emerged as a powerful framework for sequential decision-making in finance, enabling agents to learn optimal allocation policies through direct interaction with market environments.

Despite these advances, single-agent RL models face inherent limitations when applied to real-world financial systems, which are naturally decentralized and composed of multiple interacting decision-makers. This has led to growing interest in Multi-Agent Reinforcement Learning (MARL), where multiple autonomous agents operate simultaneously, either cooperatively or competitively, to achieve shared or individual objectives. Multi-agent frameworks offer improved scalability, robustness, and adaptability, making them well suited for dynamic asset allocation and portfolio optimization.

In parallel, the emergence of Large Language Models (LLMs) and agent-based reasoning systems has further expanded the scope of AI-driven finance. LLM-powered agents enable natural language understanding, sentiment analysis, macroeconomic reasoning, and explainable decision-making, complementing quantitative reinforcement learning approaches. Recent research has explored hybrid architectures that combine MARL, deep learning, and LLM-based agents to address the challenges of interpretability, adaptability, and real-time decision support. Given the rapid growth and diversification of research in this domain, a consolidated and structured review is necessary to understand the current state of the art. This review paper systematically examines existing literature on multi-agent AI frameworks for asset allocation, portfolio optimization, and financial trading, including reinforcement learning-based systems, agent-based financial architectures, and LLM-driven multi-agent models. By analyzing methodologies, performance outcomes, and practical limitations, this survey highlights prevailing trends, identifies unresolved challenges, and outlines future research directions for building intelligent, adaptive, and scalable portfolio management systems.

II. LITERATURE REVIEW

The application of Artificial Intelligence (AI) in financial markets has gained significant attention due to the increasing complexity, volatility, and non-stationary nature of asset prices. Researchers have explored a wide spectrum of approaches ranging from traditional deep learning models to reinforcement learning and, more recently, multi-agent and large language model (LLM)-based frameworks. This section presents a structured review of existing literature relevant to **asset allocation and portfolio optimization**, categorized into deep learning-based prediction models, reinforcement learning approaches, and multi-agent intelligent systems.

A. Deep Learning Approaches for Stock Prediction and Portfolio Support

Early research focused on leveraging deep learning models to predict stock prices and market trends, forming the foundation for intelligent portfolio decision-making. Long Short-Term Memory (LSTM) networks emerged as a dominant approach due to their ability to capture temporal dependencies in financial time series. Bandi et al. proposed a Stacked LSTM (SLSTM) architecture to enhance stock market prediction accuracy by learning long-term dependencies more effectively than single-layer LSTM models [1]. Their results demonstrated improved forecasting performance, although the approach relied solely on historical price data and did not incorporate dynamic portfolio allocation strategies. Reddy et al. explored the use of Recurrent Neural Networks (RNN) and LSTM models for stock price prediction, highlighting LSTM's superiority in handling sequential data and short-term forecasting tasks [2]. However, their work was limited by single-agent decision-making and lacked adaptability to sudden market regime changes. Abivarshini and France compared LSTM, Random Forest, and XGBoost models for short-term and intraday trading applications [3]. Their findings emphasized the importance of ensemble learning in improving robustness and reducing overfitting. Despite improved prediction accuracy, the study did not address sequential decision-making or dynamic portfolio rebalancing.

More advanced architectures were explored by Lee and Yoo, who introduced a Transformer-based model integrated with Time2Vec encoding to capture periodic and long-range temporal patterns in stock data [4]. The self-attention mechanism improved interpretability and robustness over traditional recurrent models, but the computational complexity remained a key challenge.

B. Reinforcement Learning for Trading and Portfolio Optimization

To overcome the limitations of static prediction models, researchers have increasingly adopted Reinforcement Learning (RL) for sequential financial decision-making. RL-based systems directly optimize portfolio returns by interacting with market environments. Pattanayak et al. applied Deep Reinforcement Learning (DRL) techniques using Deep Q-Networks (DQN) and DQN-LSTM hybrids for stock trading decisions [5]. Their work demonstrated superior adaptability and profitability compared to traditional machine learning models, although it assumed ideal trading conditions without transaction costs or liquidity constraints.

In high-frequency and blockchain-based markets, Govindasamy et al. proposed a CNN-LSTM hybrid model optimized using Adam and swarm intelligence techniques to predict cryptocurrency return rates [6]. While the model achieved strong predictive performance, it primarily focused on return estimation rather than portfolio-level optimization.

C. Multi-Agent Reinforcement Learning in Finance

Single-agent RL models face scalability and robustness limitations in real-world financial systems, which naturally involve multiple interacting decision-makers. This has led to the adoption of Multi-Agent Reinforcement Learning (MARL). A comprehensive theoretical foundation for MARL is provided by a survey on multi-agent reinforcement learning, which categorizes learning paradigms into cooperative, competitive, and mixed settings and discusses challenges such as non-stationarity, coordination, and credit assignment [7].

This work establishes the suitability of MARL for complex, decentralized environments like financial markets. Building on this foundation, MAPS (Multi-Agent Reinforcement Learning-based Portfolio Management System) introduced a cooperative MARL framework where multiple agents collaboratively learn optimal asset allocation strategies [8]. The system demonstrated improved diversification and risk-adjusted returns compared to single-agent approaches, though transaction cost modeling was limited. Further extending MARL to fast-paced environments, a study on multi-agent reinforcement learning for high-frequency trading explored competitive and cooperative agent interactions using advanced MARL algorithms [9]. The results highlighted improved execution efficiency and adaptability in highly volatile, low-latency markets, but the approach emphasized short-term trading rather than long-term portfolio stability.

D. LLM-Based and Agent-Oriented Financial Systems

Recent advances in Large Language Models (LLMs) have introduced new possibilities for reasoning, interpretability, and human-like decision-making in finance. The TradingAgents framework proposed a multi-agent system powered by LLMs, where each agent specializes in a specific financial role such as technical analysis, sentiment evaluation, macroeconomic reasoning, and risk assessment [10]. Through structured inter-agent communication, the system achieved improved interpretability and adaptability, although at a higher computational cost. A broader perspective on agent-based AI in finance is provided by a scientific review of AI agents in finance and fintech, which examines applications ranging from trading and portfolio management to fraud detection and financial advisory systems [11]. The review emphasizes the advantages of decentralized intelligence while also discussing regulatory, ethical, and deployment challenges. Complementing these works, recent research integrating LLMs with Retrieval-Augmented Generation (RAG) demonstrated that augmenting language models with real-time financial data significantly improves multi-asset portfolio construction and reduces hallucination risks [12]. While promising, such systems still require integration with optimization and reinforcement learning modules for precise asset weight allocation.

E. Research Gaps Identified

From the reviewed literature, several key gaps emerge:

1) Limited integration of multi-agent cooperation with dynamic portfolio optimization
2) Insufficient modeling of transaction costs, market impact, and real-world constraints
3) Trade-offs between interpretability and computational efficiency
4) Lack of unified frameworks combining MARL, LLM-based reasoning, and risk-aware optimization

These gaps highlight the need for a comprehensive multi-agent AI framework capable of dynamic, scalable, and explainable asset allocation across diverse market conditions.

III. COMPARITIVE ANALYSIS

Ref	Paper Title	AI Technique Used	Agent Type	Application Domain	Key Contributions	Limitations / Gaps
[1]	Stacked LSTM: A Deep Learning Model to Predict Stock Market	Stacked LSTM (Deep Learning)	Single-Agent	Stock Price Prediction	Improves long-term dependency learning; better RMSE than single LSTM	No portfolio optimization; ignores market dynamics & risk
[2]	Stock Market Prediction Using RNN	RNN, LSTM	Single-Agent	Stock Price Prediction	Demonstrates LSTM superiority over RNN for time-series	Short-term focus; no dynamic rebalancing
[3]	Stock Market Price Prediction Using Deep Learning	LSTM, Random Forest, XGBoost	Single-Agent	Intraday & Short-Term Trading	Ensemble learning improves robustness and accuracy	No sequential decision-making or portfolio-level strategy

Ref	Paper Title	AI Technique Used	Agent Type	Application Domain	Key Contributions	Limitations / Gaps
[4]	Stock Price Prediction Using Transformer and Time2Vec	Transformer + Time2Vec	Single-Agent	Stock Price Forecasting	Captures long-range & periodic dependencies; better interpretability	High computational cost; no trading strategy integration
[5]	A Deep Reinforcement Learning Technique for Stock Price Prediction and Trading Decision	DQN, DQN-LSTM	Single-Agent	Automated Trading	Adapts to market dynamics; higher profitability than ML	Assumes ideal trading conditions; lacks risk modeling
[6]	High-Frequency Stock Market Price Prediction Using Blockchain and Deep Learning	CNN-LSTM + Optimization	Single-Agent	Cryptocurrency Prediction	High accuracy in return-rate prediction	Focuses on prediction, not portfolio optimization
[7]	A Survey on Multi-Agent Reinforcement Learning and Its Applications	MARL Survey	Multi-Agent	General AI Systems	Provides MARL taxonomy and challenges	Theoretical; no direct financial implementation
[8]	MAPS: Multi-Agent Reinforcement Learning-based Portfolio Management System	MARL (Deep RL)	Multi-Agent (Cooperative)	Portfolio Management	Improves diversification and risk-adjusted returns	Limited transaction cost handling
[9]	Multi-Agent Reinforcement Learning for High-Frequency Trading Strategy Optimization	MARL (PPO, VDN)	Multi-Agent (Competitive/Cooperative)	High-Frequency Trading	Efficient execution in non-stationary markets	Short-term trading focus; infrastructure-heavy
[10]	TradingAgents: Multi-Agents LLM Financial Trading Framework	LLM-based Agents	Multi-Agent (Role-Based)	Trading & Market Analysis	High interpretability; agent specialization	High computational cost; not HFT-ready

Ref	Paper Title	AI Technique Used	Agent Type	Application Domain	Key Contributions	Limitations / Gaps
[11]	AI Agents in Finance and Fintech: A Scientific Review	Agent-Based AI Survey	Multi-Agent	Finance & FinTech	Broad overview of agent systems and future trends	No experimental validation
[12]	Leveraging LLMs and RAG for Enhanced Multi-Asset Portfolio Construction	LLM + RAG	Single/Multi-Agent Hybrid	Multi-Asset Portfolio Allocation	Reduces hallucination; supports diverse assets	Weak weight optimization; depends on external data

IV. SUMMARY OF COMPARITIVE ANALYSIS

The comparative analysis of the reviewed literature reveals a clear evolution in the application of Artificial Intelligence techniques for financial decision-making, progressing from single-agent predictive models to advanced multi-agent and language-driven frameworks. Early studies predominantly relied on deep learning models such as LSTM, RNN, CNN, and ensemble techniques to improve stock price prediction accuracy. While these approaches demonstrated strong performance in capturing temporal patterns, they remained limited to forecasting tasks and lacked mechanisms for dynamic portfolio allocation and sequential decision-making.

Subsequent research introduced reinforcement learning-based models that enabled agents to learn trading and allocation strategies through direct interaction with market environments. These models improved adaptability and profitability compared to traditional machine learning approaches; however, most of them were designed as single-agent systems and often assumed idealized market conditions without fully accounting for transaction costs, liquidity constraints, or risk management.

More recent studies have shifted toward multi-agent reinforcement learning frameworks, recognizing the decentralized and interactive nature of financial markets. Cooperative and competitive multi-agent systems have shown enhanced robustness, scalability, and risk-adjusted performance by distributing decision-making across multiple agents. Nevertheless, many of these systems focus either on short-term trading or require significant computational and infrastructural resources.

The latest research trend integrates Large Language Models and agent-based reasoning into financial systems, enabling role-based specialization, natural language understanding, and improved interpretability. While LLM-driven agents enhance explainability and strategic reasoning, they still face challenges related to computational cost, real-time deployment, and precise asset weight optimization.

Overall, the comparative study highlights a research gap in unified frameworks that combine multi-agent reinforcement learning, risk-aware portfolio optimization, and explainable AI under realistic market constraints. Addressing these limitations presents a promising direction for future research in dynamic asset allocation and intelligent portfolio management.

V. FUTURE SCOPE

Based on the insights derived from the reviewed literature, several promising directions for future research can be identified:

1) Unified Multi-Agent Frameworks: Future studies should focus on developing integrated architectures that combine multi-agent reinforcement learning, deep learning, and LLM-based reasoning to support dynamic asset allocation under diverse market conditions.
2) Risk-Aware and Constraint-Based Optimization: Incorporating realistic constraints such as transaction costs, market impact, liquidity limitations, and regulatory compliance into learning frameworks remains an open challenge and a critical requirement for real-world deployment.
3) Explainable and Interpretable AI Systems: Enhancing transparency and interpretability through explainable AI (XAI) techniques and language-based reasoning agents will be essential for increasing trust and adoption in financial institutions.
4) Scalability and Real-Time Deployment: Research is needed to address the computational complexity of multi-agent and LLM-driven systems, enabling scalable, low-latency solutions suitable for real-time portfolio management.

5) Hybrid Human–AI Decision Systems: Future frameworks may explore collaborative human–AI decision-making, where intelligent agents assist investors and portfolio managers through interactive, adaptive, and personalized recommendations.
6) Cross-Market and Multi-Asset Extensions: Expanding existing models to operate across multiple asset classes and global markets can

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VI. CONCLUSION

This review paper presented a comprehensive analysis of recent advancements in Artificial Intelligence–based approaches for dynamic asset allocation and portfolio optimization, with particular emphasis on reinforcement learning, multi-agent systems, and agent-oriented financial frameworks. The surveyed literature demonstrates a clear transition from traditional deep learning models focused on stock price prediction toward more adaptive, decision-driven methodologies capable of operating in highly volatile and non-stationary financial environments. Early deep learning approaches such as LSTM, CNN, ensemble models, and Transformer-based architectures significantly improved forecasting accuracy by capturing complex temporal dependencies in financial time-series data. However, these models were primarily limited to predictive tasks and lacked the ability to perform sequential decision-making or adaptive portfolio rebalancing. Reinforcement learning methods addressed this limitation by enabling agents to directly learn optimal trading and allocation strategies through interaction with market environments, thereby improving adaptability and profitability.

More recent studies employing multi-agent reinforcement learning (MARL) have shown that decentralized, cooperative, and competitive agent interactions can enhance robustness, scalability, and risk-adjusted returns. Additionally, the integration of Large Language Models (LLMs) into agent-based financial systems has introduced new capabilities in interpretability, strategic reasoning, and role-based specialization. Despite these promising developments, existing approaches often rely on simplified market assumptions, incur high computational costs, or lack unified frameworks that simultaneously address scalability, explainability, and real-world trading constraints. Overall, this review highlights that while AI-driven financial systems have achieved substantial progress, there remains a need for holistic and practical solutions that can operate reliably in real-world financial markets.

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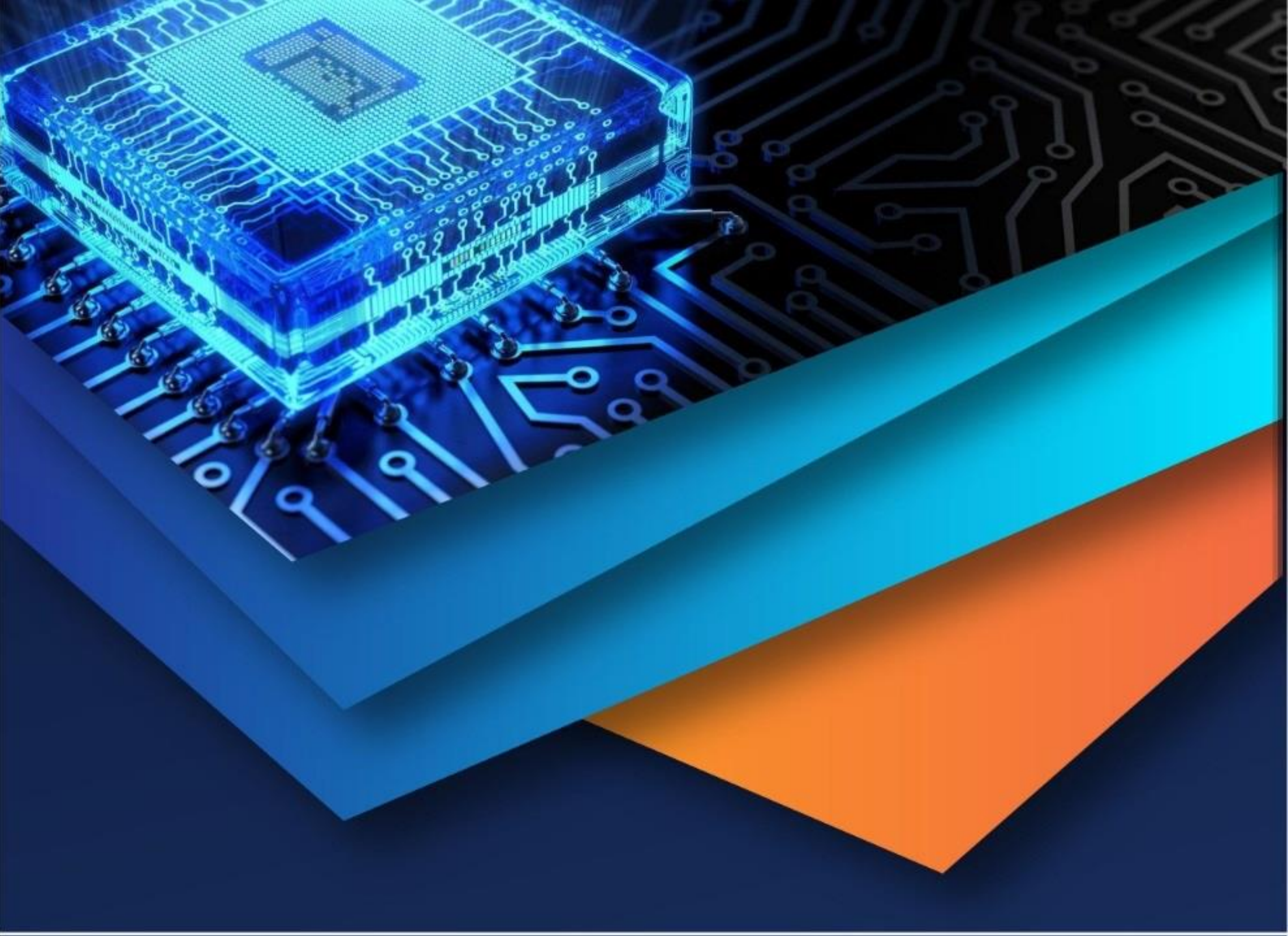

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