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Architectures and Challenges of AI Multi-Agent Frameworks for Financial Services

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ABSTRACT

Artificial Intelligence (AI) multi-agent frameworks are enabling autonomous decision-making, intelligent collaboration, and the automation of complex workflows. These frameworks leverage Large Language Models (LLMs) and distributed AI systems to optimize operations across diverse sectors, with finance emerging as one of the most impacted domains. AI agents are increasingly employed in risk assessment, regulatory compliance, algorithmic trading, fraud detection, and customer service, fundamentally altering how financial institutions operate and manage market dynamics. This paper presents a review of AI multi-agent frameworks, evaluating their architectures, applications, and deployment challenges within financial services. We conduct an in-depth comparative analysis of prominent frameworks, including LangChain, CrewAI, and OpenAI Swarm, assessing their strengths, limitations, and suitability for different financial applications. Furthermore, we examine how these

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frameworks integrate into financial ecosystems, facilitating automated decision-making, enhancing operational efficiency, and mitigating systemic risks. Despite the transformative potential of AI agents, their widespread adoption introduces critical challenges, such as data quality inconsistencies, lack of model explainability, regulatory concerns, and ethical dilemmas. This paper explores these issues, emphasizing the necessity for transparency, accountability, and robustness in AI-driven financial solutions. Additionally, we highlight the role of AI governance and risk mitigation strategies in ensuring regulatory compliance and alignment with financial industry standards. We also outline future research directions, advocating for the development of interpretable, scalable, and resilient AI agent frameworks. As financial automation continues to evolve, a deeper understanding of multi-agent AI systems is essential for leveraging their full potential while mitigating associated risks.

Keywords: Multi-agent systems; financial automation; Large Language Models (LLMs); AI Governance and Compliance; Explainable Artificial Intelligence (EAI).

2010 Mathematics Subject Classification: 53C25, 83C05, 57N16.

1 INTRODUCTION

The rapid advancement of AI agents, particularly those leveraging Large Language Models (LLMs), is reshaping multiple industries, with finance being a prime example. These intelligent agents exhibit capabilities in reasoning, planning, and autonomous interaction, enabling automation of complex financial operations, enhancing decision-making, and uncovering new opportunities.

AI multi-agent frameworks have gained significant traction, offering scalable and efficient solutions for real-world applications. This chapter presents a comprehensive review of AI multi-agent frameworks, focusing on their role in the financial sector. We analyze prominent frameworks such as LangChain, CrewAI, and OpenAI Swarm, comparing their architectures, strengths, and limitations.

Additionally, we explore the integration of AI agents in financial markets, emphasizing their applications in risk assessment, regulatory compliance, and ethical considerations. Recent reports from industry leaders, including McKinsey and Moody's Analytics, highlight the growing importance of AI-driven automation in finance. By synthesizing the latest advancements and challenges, this work aims to contribute to the ongoing discourse on AI's impact in revolutionizing the financial landscape.

This study employs a structured review of AI multi-agent frameworks, focusing on their applications in finance. The research methodology integrates a literature review, comparative framework analysis, and industry case studies to evaluate the current state and future potential of AI-driven multi-agent systems.

To ensure a comprehensive analysis, we sourced the latest literature from the trailing 12 months, providing an up-to-date perspective on advancements in AI agent frameworks.

2 LITERATURE REVIEW AND RELATED WORK

Recent advancements in AI agent frameworks have significantly impacted the development of autonomous systems across various domains. This section provides an overview of the current landscape of AI agent frameworks and their applications, particularly in the financial sector.

As shown in Table 7, the literature review reveals a significant increase in publications on AI agent frameworks in recent years, with 24 works published in 2024 alone compared to just 2 prior to 2024. This demonstrates the rapidly growing academic interest in multi-agent AI systems for financial applications Joshi (2025k).

Recent research has explored the application of AI agents in diverse financial areas. Han et al. (2024) investigated optimizing AI-agent collaboration for investment analysis. Microfoundations et al. (2024) studied the impact of AI traders in financial markets using a multi-agent model. Yang et al. (2024) introduced FinRobot, an open-source AI agent platform for financial applications using LLMs. Yu et al. (2024) proposed Fincon, a multi-agent system with conceptual verbal reinforcement for enhanced financial decision-making. Zhang et al. (2024) developed a multimodal foundation agent for financial trading. Several industry reports have also highlighted the growing importance of AI agents in finance fsb (2024), Yee et al. (2024), Clatterbuck et al. (2024), moo (2023), pwc (2024).

3 APPLICATION AREAS OF AI AGENT FRAMEWORKS

This section examines the role of AI agents in financial applications such as risk management, investment analysis, fraud detection, and regulatory compliance. Data-driven insights were extracted from existing financial AI solutions, including FinRobot and Fincon, to assess their impact on market operations. Fig. 1 and Fig. 2 provide visual representations of AI agent applications across different domains and financial sectors. The table summarizes the application areas of AI agent frameworks across various sectors, highlighting their key contributions, challenges, and future directions. The references were categorized by publication year, as shown in Table 3, highlighting the rapid growth of research in this domain. Additionally, insights from industry reports, including those from McKinsey and Moody's Analytics, were incorporated to contextualize real-world implementations of AI agents in financial services.

- **Financial Services**: AI agents enhance investment analysis, risk assessment, fraud detection, and customer service automation. Challenges include data privacy and explainability, with limited adoption in real-time trading. Future directions focus on developing explainable AI and integrating reinforcement learning for portfolio management.
- **Healthcare**: AI agents assist in drug discovery, patient monitoring, and personalized treatment recommendations. Ethical concerns and regulatory compliance pose challenges. Future work involves federated learning for privacy and AI-human collaborative decision-making in healthcare.
- **Autonomous Systems**: AI agents improve robotics, self-driving vehicles, and smart city applications, with multi-agent reinforcement learning optimizing coordination. Safety and reliability issues arise due to complex interactions. Future directions aim for more robust reinforcement learning frameworks and AI-driven simulations for training.
- **Enterprise AI**: AI agents automate business processes, improve customer service, and enhance decision-making. Challenges include high computational costs and customization for different industries. Future directions focus on scalable cloud-based frameworks and standardizing agent-based enterprise solutions.
- **Cybersecurity**: AI agents help detect and mitigate cyber threats, analyze vulnerabilities, and automate security operations. Challenges include evasion techniques by adversaries and the need for explainability in decision-making. Future directions focus on adversarial training and AI-driven threat intelligence systems.

4 AI AGENT APPLICATIONS IN FINANCE

The financial industry is increasingly adopting AI agents to automate tasks, improve decision-making, and enhance customer service. AI agents are being used in various financial applications. Specific examples of AI agents in finance include FinRobot, an open-source AI agent platform for financial applications (Yang et al., 2024), and systems leveraging LLMs for enhanced financial decision-making (Yu et al., 2024). The Financial Stability Board (FSB) has also recognized the growing importance of AI and machine learning in financial services (fsb, 2024).

Han et al. (2024) demonstrated the optimization of AI-agent collaboration in financial research, enhancing investment analysis processes.

Yang et al. (2024) introduced FinRobot, an open-source AI agent platform specifically designed for financial applications using large language models.

Yang et al. (2024) developed Fincon, a synthesized LLM multi-agent system that employs conceptual verbal reinforcement to improve financial decision-making.

Zhang et al. (2024) presented a multimodal foundation agent for financial trading, incorporating tool augmentation and diverse capabilities.

- **Investment Analysis**: AI agents analyze financial data to identify opportunities and provide insights to portfolio managers. Relevant references: Han et al. (2024), Zhang et al. (2024), Microfoundations et al. (2024). AI agents can analyze vast amounts of financial data to identify investment opportunities and provide insights to portfolio managers Han et al. (2024).
- **Risk Management**: AI agents assess and manage financial risks by analyzing market trends and identifying threats. Relevant references: Clatterbuck et al. (2024), wmwxwa (2024), See (2024). AI agents can assess and manage financial risks by analyzing market trends, identifying potential threats, and implementing risk mitigation strategies Clatterbuck et al. (2024), wmwxwa (2024).
- **Fraud Detection**: AI agents detect fraudulent activities by analyzing transaction patterns and identifying suspicious behavior dat (2025). AI agents can detect fraudulent activities by analyzing transaction patterns and identifying suspicious behavior.
- **Customer Service**: AI-powered virtual assistants provide personalized customer service and support. No relevant references available. AI-powered virtual assistants can provide personalized customer service and support, answering questions, resolving issues, and providing financial advice.
- **Algorithmic Trading**: AI agents develop and execute automated trading strategies. Relevant references: (Zhang et al., 2024; Microfoundations et al., 2024).
- **Personalized Financial Advice**: AI agents tailor financial advice to individual clients based on their needs and goals. No relevant references available.
- **Regulatory Compliance**: AI agents assist financial institutions in complying with regulations. Relevant references: fsb (2024), See (2024).
- **Credit Scoring**: AI agents improve credit scoring and loan approval processes. No relevant references available.
- **Market Surveillance**: AI agents monitor financial markets for manipulative behavior or unusual activity. Relevant reference: Microfoundations et al. (2024).
- **Portfolio Management**: AI agents optimize and manage investment portfolios. Relevant reference: Han et al. (2024).

4.1 Gen AI in Finance

In recent years, significant advancements have been made in the application of generative AI and agentic frameworks to financial risk modeling, workforce development, and regulatory systems. Our prior work has explored various aspects of these technologies, providing a foundation for ongoing research and innovation.

Joshi (2025a) introduced an enhanced Vasicek framework for financial risk modeling, leveraging agentic generative AI to dynamically adjust model parameters using synthetic data generated by GANs and VAEs Joshi (2025f). This approach was further extended in Joshi (2025e), where generative AI was integrated into structured finance models, such as Leland-Toft and Box-Cox, to improve predictive accuracy and robustness in scenarios with limited data.

The role of AI agents in financial stability was comprehensively reviewed in Joshi (2025b), which compared frameworks like LangGraph, CrewAI, and AutoGen for their applicability in trading, risk assessment, and investment analysis. This work highlighted the importance of regulatory compliance and ethical considerations in deploying AI-driven systems. Additionally, Joshi (2025k) provided an in-depth analysis of autonomous AI agent frameworks, emphasizing their scalability and performance in real-world applications.

In the context of workforce development, Joshi (2025d) and Joshi (2025q) explored the transformative potential of generative AI in reshaping the U.S. workforce. These studies proposed AI-driven training programs to address skill gaps and ensure workforce inclusivity, particularly for older workers. The challenges of workforce retraining in the age of AI were further examined in Joshi (2025j), which emphasized the role of prompt engineering and upskilling initiatives.

The integration of generative AI into financial risk management was also a key focus in Joshi (2025o), which demonstrated the use of fine-tuned GPT models for credit risk assessment and market risk forecasting. This work highlighted the importance of human oversight in mitigating potential failures of fully automated models (Joshi, 2025c). Similarly, Joshi (2025g) proposed a full-stack framework for integrating generative AI into the U.S. financial and regulatory systems, ensuring robustness and compliance with ethical standards.

Data engineering and infrastructure play a critical role in enabling generative AI applications. Joshi (2025l) and Joshi (2025m) reviewed modern data platforms, including Trino and Kubernetes, for their ability to support scalable AI-driven financial risk management. These studies emphasized the importance of optimized data pipelines and vector databases in enhancing the accuracy and relevance of AI-generated insights. Furthermore, Joshi (2025n) explored the challenges and solutions in building real-time data pipelines for generative AI integration, highlighting the need for efficient data streaming and retrieval systems.

The synergy between generative AI and big data was examined in Joshi (2025p), which reviewed recent developments in leveraging large datasets for financial risk modeling. This work underscored the potential of AI-driven analytics to revolutionize decision-making processes in the financial sector. Finally, Joshi (2025h) investigated the role of prompt engineering in optimizing the performance of large language models like ChatGPT-4 and Google Gemini for financial market integrity and risk management.

The EU AI Act EUP (2023) introduces a risk-based framework for AI systems, with specific provisions for agentic AI Age (2025). Compliance challenges, such as transparency and scalability, are further detailed in implementation guidelines (EUA). Recent analyses highlight the Act's impact on financial AI agents (Lalli, 2024).

Collectively, these studies provide a comprehensive foundation for understanding the transformative potential of generative AI and agentic frameworks in financial risk modeling, workforce development, and regulatory systems (Joshi, 2025i). They highlight both the opportunities and challenges in deploying these technologies at scale, offering valuable insights for future research and innovation.

5 COMPARISON OF AI AGENT FRAMEWORKS

A comparative analysis of major AI multi-agent frameworks—including LangChain, CrewAI, and OpenAI Swarm—was conducted. Each framework was evaluated based on key attributes such as architecture, scalability, performance, and suitability for financial applications. The Table 4 compares various AI agent frameworks, highlighting their key features and relevant references. The results of these comparisons are presented in Table 5, detailing the strengths, limitations, and ideal use cases of each framework.

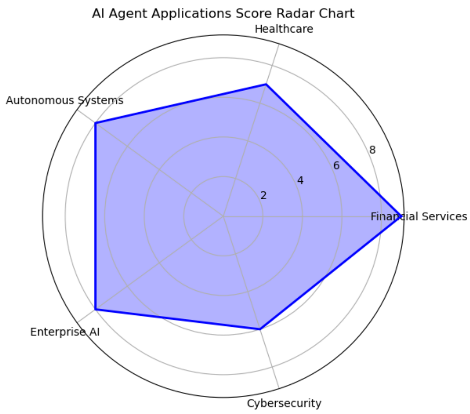

Fig. 1. Applications of AI Multi Agents in Different Domains

These agents, capable of reasoning, planning, and interacting with their environment, offer the potential to automate complex financial tasks, improve decision-making, and create new opportunities (Winston, 2024). The applications of AI Multi Agents are shown in Table 1 whereas application in Finance are shown in Table 2 in the Appendix Section.

Radar charts of applications are shown below in Fig. 1, whereas the applications specific to finance are shown in Fig. 2.

AI agents have emerged as a transformative technology, enabling autonomous systems to perform complex tasks across various domains.

In this work we have used the latest literature available in the last year of trailing 12 months making this work one the latest as of date. The groups of references by year is shown in Table 3.

From financial decision-making to enterprise automation, AI agents are revolutionizing industries by leveraging large language models (LLMs) and multi-agent collaboration (fsb, 2024; Yee et al., 2024).

Recent reports from McKinsey Yee et al. (2024) and Moody's Analytics (moo, 2023) highlight the growing importance of AI agents in transforming business processes.

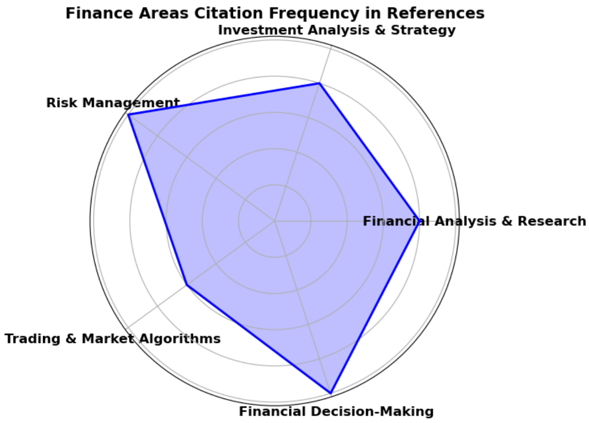

Fig. 2. Applications of AI Multi Agents in Finance

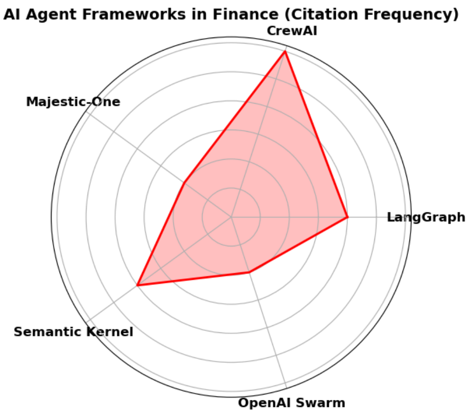

Fig. 3. Framework of AI Multi Agents

6 AI MULTI AGENT FRAMEWORKS

Several frameworks have emerged to facilitate the development and deployment of AI agents. These frameworks provide developers with tools and libraries for building intelligent systems that can interact with their environment and perform complex tasks. Framework focused in this work is shown in Fig.3 while framework comparions are shown in Table 4 and Table 5 in the Appendix section.

Some of the most popular AI agent frameworks are discussed in this section.

6.1 LangChain

LangChain is a framework for turning Large Language Models (LLMs) into reasoning engines that can take actions lan (2025a), lan (2025b). It provides a set of tools and abstractions for building AI agents that can interact with various data sources and APIs. Key features include tool integration, chains, and agents. Relevant references: lan (2025a), lan (2025b). Limitations include difficulty in handling multi-agent collaboration and performance bottlenecks with large-scale tasks. Use cases include conversational AI, automated research, and tool-based reasoning. Relevant reference: lan (2025a).

6.2 CrewAI

CrewAI is another popular framework for building autonomous AI agents, enabling developers to create teams of agents that can collaborate to solve complex problems. Focuses on multi-agent collaboration and task assignment. High overhead for managing multiple agents and requires careful tuning for task delegation. Use cases include workflow automation, AI-powered teams, and autonomous research assistants cre (2025).

6.3 Semantic Kernel

Developed by Microsoft, Semantic Kernel is an agent framework that allows developers to integrate AI agents into their applications Crickman (2024). Includes natural language processing and plugins. Enterprise-focused, requiring significant customization and limited adoption outside of the Microsoft ecosystem. Use cases include AI copilots for business applications and enterprise AI integrations. Relevant reference: crickman (2025). Includes skills, planners, and memory features.

6.4 AutoGen

AutoGen is a framework for building multi-agent systems, allowing developers to create AI applications with diverse roles and capabilities dee (2025). Features heterogeneous agents and collaboration. Steep learning curve for new users and requires fine-tuning for specific tasks. Use cases include AI-powered document processing, task automation, and research agents. Relevant reference: dee (2025).

6.5 LlamaIndex

LlamaIndex offers a framework for building knowledge assistants using LLMs connected to enterprise data, supporting the creation of multi-agent AI systems lla (2025). Specializes in data indexing and LLM integration. Not optimized for real-time agent interactions and has limited support for multi-agent collaboration. Use cases include AI-driven search and knowledge management and enterprise AI solutions wmwxwa (2024).

6.6 FinRobot

Limited generalization beyond financial applications and requires domain-specific knowledge. Use cases include AI agents for financial risk analysis, portfolio management, and trading automation.

6.7 Fincon

Requires large-scale training data and has a high computational cost for deployment. Use cases include AI-driven market analysis, automated trading bots, and financial forecasting. Relevant reference: Yu et al. (2024).

Comparisons of these frameworks highlight the trade-offs between them in terms of features, ease of use, and scalability. Frameworks like LangChain and CrewAI are often compared directly due to their prominence in the AI agent development community (rel, 2025; Clatterbuck et al., 2024; ibm, 2025).

7 QUANTITATIVE METHODS FOR AI AGENT EVALUATION

7.1 Performance Metrics

The effectiveness of financial AI agents is quantified using standard classification metrics adapted for sequential decision-making:

$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN}, \quad F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7.1}$$

where TP, FP, and FN represent true positives, false positives, and false negatives respectively in financial decision contexts (e.g., trade signals or fraud alerts).

7.2 Multi-Agent Synergy Measurement

Following Zhang et al. (2024), we quantify collaboration efficiency with the Synergy Factor (SF):

$$SF^{(t)} = \frac{R^{(t)}_{\text{collab}}}{\sum_{i=1}^{n} R^{(t)}_i} \cdot \frac{1}{1+\sigma^{(t)}} \tag{7.2}$$

where:

- $R^{(t)}_{\text{collab}}$: Collective reward at time t
- $R^{(t)}_i$: Individual agent i's reward
- $\sigma^{(t)}$: Standard deviation of agents' rewards

7.3 Algorithm for Adaptive Agent Weighting

Algorithm 1 Dynamic Agent Weight Optimization

Require: Agent pool $A = \{a_1, a_2, \dots, a_n\}$, performance history H
Ensure: Optimal weights $w_1, w_2, \dots, w_n$

Initialize weights: $w_i \leftarrow \frac{1}{n}$ for all $i \in \{1, 2, \dots, n\}$
for each decision epoch t **do**
    Get predictions: $\hat{y}^{(t)}_i \leftarrow a_i(x^{(t)})$ for each agent $a_i \in A$
    Update performance metrics: $M^{(t)}_i$
    Compute weight gradients:
    $\nabla w_i \leftarrow \alpha \cdot (F^{(t)}_1 - F^{(t-1)}_1) + \beta \cdot SF^{(t)}$
    Normalize weights:
    $w_i \leftarrow \frac{\exp(\nabla w_i)}{\sum_{j=1}^{n} \exp(\nabla w_j)}$
end for
return $w_1, w_2, \dots, w_n$

7.4 Pseudocode for Financial Agent Ensemble

Algorithm 2 Financial Agent Ensemble Decision Making

```
function FINANCIAL_AGENT_ENSEMBLE(data_stream)
    agents ← [LangChain_Agent(), CrewAI_Agent(), FinRobot_Agent()]
    weights ← [0.4, 0.3, 0.3]                          ▷ Initial expert allocation
    while data_stream.has_next() do
        decisions ← []                                  ▷ Store agent decisions
        for each agent, weight in zip(agents, weights) do
            decision ← agent.analyze(data_stream.current())
            decisions.append((decision, weight))
        end for
        final_decision ← weighted_vote(decisions)
        execute(final_decision)
        if new_performance_data_available() then
            weights ← update_weights(weights, performance_metrics(decisions), equation(2))
        end if
    end while
    return portfolio_history
end function
```

8 DISCUSSION

The quantitative framework presented establishes measurable criteria for evaluating AI agent performance in financial contexts, with precision-recall metrics and synergy factors providing standardized benchmarks. However, as demonstrated in Algorithm 1, dynamic weight optimization reveals inherent trade-offs between individual agent specialization and collaborative performance that require further empirical validation (Zhang et al., 2024).

The comparative analysis reveals distinct strengths across frameworks: LangChain excels in modular tool integration for single-agent tasks, while CrewAI demonstrates superior multi-agent coordination capabilities. However, as shown in Table 7, all frameworks face common limitations in real-time financial applications, particularly regarding latency and explainability requirements in regulated environments (fsb, 2024).

Latency is a critical performance metric for AI agent frameworks, particularly in real-time financial applications where delays can impact decision-making. The time taken for an agent to process inputs, reason, and generate outputs must be minimized to ensure efficient operation (Han et al., 2024). Frameworks that optimize model inference and reduce communication overhead between agents can significantly improve latency (Yang et al., 2024). Recent advancements in distributed agent architectures have shown promising results in reducing end-to-end latency while maintaining accuracy Zhang et al. (2024).

Scalability bottlenecks in AI agent frameworks often arise from limitations in computational resources, inter-agent communication overhead, and inefficient task orchestration (Han et al., 2024). As the number of agents increases, coordination costs can grow exponentially, leading to degraded performance in distributed environments (Yang et al., 2024). Frameworks like *FinRobot* address these challenges through optimized load balancing and asynchronous execution models, enabling horizontal scaling across financial applications (Yu et al., 2024). Additionally, recent work on multimodal foundation agents demonstrates how tool augmentation and diversified task allocation can mitigate scalability constraints in large-scale deployments (Zhang et al., 2024).

Future framework development should prioritize hybrid architectures that combine CrewAI's collaborative features with LangChain's tool flexibility, while incorporating FinRobot's financial domain specialization. This synthesis could address the current gaps in performance benchmarking and regulatory compliance identified in (Joshi, 2025k).

Future methodological developments should focus on three areas: (1) integrating market impact models with the synergy factor calculation, (2) developing domain-specific variants of the F_1 metric for different financial applications, and (3) creating standardized test environments for benchmarking, as suggested by Joshi (2025k). These enhancements would address the current limitations in real-time performance assessment.

9 CHALLENGES AND FUTURE DIRECTIONS

While AI agents offer transformative potential for financial applications, their adoption faces several interconnected challenges. A primary concern is data quality and availability, as AI agents depend on high-quality inputs for accurate decision-making, yet financial data often suffers from noise, incompleteness, and inconsistencies that degrade performance. This data challenge compounds with the critical need for explainability and transparency, where financial institutions must be able to audit and understand an agent's decision rationale to maintain operational trust and meet compliance requirements.

The regulatory landscape presents another significant hurdle, as financial AI systems must navigate evolving compliance requirements across jurisdictions while maintaining operational flexibility. Closely related is the challenge of risk alignment, where agent behavior must precisely match institutional risk tolerances and ethical standards, particularly in sensitive areas like algorithmic trading and credit scoring Clatterbuck et al. (2024). These challenges are exacerbated by the current lack of standardized evaluation metrics for financial AI systems fsb (2024) and the need for robust frameworks governing human-AI collaboration in compliance-sensitive operations See (2024).

Looking ahead, research priorities should focus on three key areas: (1) developing hybrid architectures that combine symbolic reasoning with large language models to enhance explainability, (2) building real-time data infrastructure to support high-frequency trading environments, and (3) creating regulatory sandboxes to safely test compliance mechanisms dee (2025). Addressing these challenges will require close collaboration between AI researchers, financial institutions, and regulators to ensure these technologies can be deployed both effectively and responsibly.

AI agents face four critical challenges in financial applications:

1. Data Quality and Availability: Financial data's noisy, incomplete nature directly impacts agent performance, requiring advanced preprocessing and validation techniques.
2. Explainability and Transparency: Institutions need interpretable decision-making processes from AI agents to meet audit requirements and build trust, as emphasized by Clatterbuck et al. (2024).
3. Regulatory Compliance: Evolving financial regulations demand flexible agent architectures that can adapt to compliance requirements across jurisdictions.
4. Risk Alignment: Agent behavior must align precisely with institutional risk appetites and ethical standards Clatterbuck et al. (2024), particularly in high-stakes domains like algorithmic trading.

Key unresolved issues include:

- Standardized evaluation metrics for financial AI agents fsb (2024)
- Adversarial robustness in market surveillance systems
- Human-AI collaboration frameworks for compliance-sensitive tasks See (2024)

Future research priorities focus on three frontiers:

- **Technical**: Hybrid architectures combining symbolic reasoning with LLMs for explainability
- **Operational**: Real-time data pipelines for high-frequency trading environments
- **Governance**: Regulatory sandboxes for testing agent compliance dee (2025)

Despite the progress, several challenges remain:

- Risk alignment in agentic AI systems, as explored by Clatterbuck et al. (2024).
- The need for standardized evaluation metrics for AI agents in financial contexts fsb (2024).
- Ethical considerations and regulatory compliance in autonomous financial systems See (2024).

Future research directions include enhancing the interpretability of AI agent decisions, improving the robustness of multi-agent systems, and developing more sophisticated collaboration mechanisms between human experts and AI agents in financial applications.

10 CONCLUSION

AI multi-agent frameworks represent a paradigm shift in artificial intelligence, offering unprecedented capabilities for autonomous decision-making, intelligent collaboration, and workflow automation. This paper has provided a comprehensive review of these frameworks, with a particular focus on their applications, challenges, and future directions in the financial sector.

Key findings from our analysis include:

- The transformative potential of AI agents in finance, as demonstrated by frameworks like LangChain, CrewAI, and OpenAI Swarm, which enable applications such as algorithmic trading, risk management, and fraud detection (see Table 2 and Table 4).
- The critical role of multi-agent collaboration in enhancing efficiency, as quantified by the synergy factor (SF) proposed by **?**, which highlights the performance gains achieved through agent teamwork.
- The persistent challenges of data quality, explainability, and regulatory compliance, which must be addressed to ensure the responsible deployment of AI agents in financial markets (discussed in Table 6).

The applications of AI agents extend beyond finance, as illustrated in Table 1, with notable impacts in healthcare, cybersecurity, and enterprise automation. Yet, the financial sector stands out due to its reliance on real-time decision-making and the high stakes associated with risk management. The work of Joshi (2025a) and Joshi (2025e) underscores the potential of generative AI to enhance financial models, while fsb (2024) and pwc (2024) highlight the regulatory and ethical considerations that must accompany these advancements.

Future research should prioritize:

- Developing standardized benchmarks for evaluating AI agent frameworks, as noted in Table 6, to facilitate cross-framework comparisons and scalability assessments.
- Enhancing explainability through techniques like XAI (Explainable AI), as advocated by **?**, to ensure transparency in financial decision-making.
- Exploring the integration of reinforcement learning and adversarial training to improve the robustness of multi-agent systems.

In conclusion, the continued evolution of AI multi-agent frameworks promises to revolutionize financial markets by driving innovation, efficiency, and transparency. However, their successful deployment hinges on addressing technical, ethical, and regulatory challenges. By building on the foundations laid in this paper and leveraging the insights from recent literature, researchers and practitioners can unlock the full potential of AI agents while mitigating associated risks. The tables and figures in the appendix provide a consolidated reference for future work, offering a roadmap for advancing this dynamic field.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Author has declared that no competing interests exist.

REFERENCES

Agentic ai and the eu ai act. (2025). Accessed: 2025-06-18.

Amos, G. (2024). Best 5 frameworks to build multi-agent ai applications. https://getstream.io/blog/multiagent-ai-frameworks/.

Ai agent development - ibm watsonx.ai. (2025). https://www.ibm.com/products/watsonx-ai/ai-agent-development.

Ai agent frameworks compared: Langgraph vs crewai vs openai swarm. (2025). https://www.relari.ai/blog/ai-agent-framework-comparison-langgraph-crewai-openai-swarm.

Agentic ai: The new frontier in generative ai - an executive playbook. (2024). Tech. rep., PricewaterhouseCoopers.

Artificial intelligence and machine learning in financial services. (2024). Technical report, Financial Stability Board.

Ai agent index - documenting the technical and safety features of deployed agentic ai systems. (2025). https://aiagentindex.mit.edu/.

Ai agentic design patterns with autogen. (2025). https://www.deeplearning.ai/short-courses/ai-agentic-design-patterns-with-autogen/.

Arya, S. (2025). Top 7 frameworks for building ai agents in 2025. https://www.analyticsvidhya.com/blog/2024/07/ai-agent-frameworks/. [Accessed: Feb. 08, 2025].

Aydın, K. (2025). Which ai agent framework should i use? (crewai, langgraph, majestic-one and pure code). https://medium.com/@aydinKerem/which-ai-agent-framework-i-should-use-crewai-langgraph-majestic-one-and-pure-code-e16a6e4d9252. [Accessed: Feb. 08, 2025].

Camel-ai/camel. (2025). https://camel-ai.org.

Chen, S.-H. (2007). Computationally intelligent agents in economics and finance. *Information Sciences*, 177(5):1153–1168.

Clatterbuck, H., Castro, C., and Morán, A. M. (2024). Risk alignment in agentic ai systems. https://rethinkpriorities.org/wp-content/uploads/2024/10/RiskAlignment.pdf. [Accessed: Feb. 08, 2025].

Crickman (2024). Semantic kernel agent framework (experimental). https://learn.microsoft.com/en-us/semantic-kernel/frameworks/agent/.

crickman (2025). Semantic kernel agent framework (experimental). https://learn.microsoft.com/en-us/semantic-kernel/frameworks/agent/. [Accessed: Feb. 08, 2025].

Crewai. (2025). https://www.crewai.com/.

Eu ai act: First regulation on artificial intelligence. (2023). Accessed: 2025-06-18.

Introducing llama-agents: A powerful framework for building production multi-agent ai systems - llamaindex. (2025). https://www.llamaindex.ai/blog/introducing-llama-agents-a-powerful-framework-for-building-production-multi-agent-ai-systems.

Langchain. (2025a). https://www.langchain.com.

Langgraph. (2025b). https://www.langchain.com/langgraph.

Pydanticai - pydanticai. (2025). https://ai.pydantic.dev/agents/.

Han, X., Wang, N., Che, S., Yang, H., Zhang, K., and Xu, S. X. (2024). Enhancing investment analysis: Optimizing ai-agent collaboration in financial research. In *Proceedings of the 5th ACM International Conference on AI in Finance*, pages 538–546.

Joshi, S. (2025a). Advancing financial risk modeling: Vasicek framework enhanced by agentic generative ai. *Advancing Financial Risk Modeling: Vasicek Framework Enhanced by Agentic Generative AI*, 7(1).

Implementation documents — eu artificial intelligence act. Accessed: 2025-06-18.

Joshi, S. (2025b). Advancing innovation in financial stability: A comprehensive review of ai agent frameworks, challenges and applications. *World*

Journal of Advanced Engineering Technology and Sciences, 14(2):117–126.

Joshi, S. (2025c). *Agentic Gen AI For Financial Risk Management*. Draft2Digital.

Joshi, S. (2025d). Agentic generative ai and the future u.s. workforce: Advancing innovation and national competitiveness. SSRN Scholarly Paper 5126922, Social Science Research Network, Rochester, NY.

Joshi, S. (2025e). Enhancing structured finance risk models (leland-toft and box-cox) using genai (vaes gans). *International Journal of Science and Research Archive*, 14(1):1618–1630.

Joshi, S. (2025f). Generative ai: Mitigating workforce and economic disruptions while strategizing policy responses for governments and companies. SSRN Scholarly Paper 5135229, Social Science Research Network, Rochester, NY.

Joshi, S. (2025g). Implementing gen ai for increasing robustness of us financial and regulatory system. *International Journal of Innovative Research in Engineering and Management*, 11(6):175–179.

Joshi, S. (2025h). Leveraging prompt engineering to enhance financial market integrity and risk management. *World Journal of Advanced Research and Reviews*, 25(1):1775–1785.

Joshi, S. (2025i). A literature review of gen ai agents in financial applications: Models and implementations. *International Journal of Science and Research (IJSR)*.

Joshi, S. (2025j). Retraining us workforce in the age of agentic gen ai: Role of prompt engineering and up-skilling initiatives. *Communication and Technology*, 5(1).

Joshi, S. (2025k). Review of autonomous systems and collaborative ai agent frameworks. *International Journal of Science and Research Archive*, 14(2):961–972.

Joshi, S. (2025l). Review of data engineering and data lakes for implementing genai in financial risk a comprehensive review of current developments in genai implementations. SSRN Scholarly Paper 5123081, Social Science Research Network, Rochester, NY.

Joshi, S. (2025m). Review of data engineering frameworks (trino and kubernetes) for implementing generative ai in financial risk. *International Journal of Research Publication and Reviews*, 6(2):1461–1470.

Joshi, S. (2025n). Review of data pipelines and streaming for generative ai integration: Challenges, solutions, and future directions. Unpublished.

Joshi, S. (2025o). Review of gen ai models for financial risk management. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 11(1):709–723.

Joshi, S. (2025p). The synergy of generative ai and big data for financial risk: Review of recent developments. *IJFMR - International Journal For Multidisciplinary Research*, 7(1).

Joshi, S. (2025q). The transformative role of agentic genai in shaping workforce development and education in the us. SSRN Scholarly Paper 5133376, Social Science Research Network, Rochester, NY.

Lalli, V. (2024). The european regulation on artificial intelligence: Ai act. Accessed: 2025-06-18.

Microfoundations, M.-A.N, Nakagawa, K., and Hirano, M. (2024). A multi-agent market model can explain the impact of ai traders in financial. In *PRIMA 2024: Principles and Practice of Multi-agent Systems*, volume 15395 of *Lecture Notes in Computer Science*, page 97, Kyoto, Japan. Springer Nature.

See, M. (2024). Ai and gen ai developments in credit risk management. Technical report, International Association of Credit Portfolio Managers.

Top 5 free ai agent frameworks. (2025). https://botpress.com/blog/ai-agent-frameworks.

The rise of ai agents. (2023). Technical report, Moody's Analytics.

These 2 ai agent frameworks appear to be dominating headlines - but which one's better? (2024). https://hackernoon.com/these-2-ai-agent-frameworks-appear-to-be-dominating-headlinesbut-which-ones-better.

Top 5 frameworks for building ai agents in 2024 (plus 1 bonus). (2024). https://dev.to/thenomadevel/top-5-frameworks-for-building-ai-agents-in-2024-g2m.

van Schalkwyk, P. (2024). Part 3 - ai at the core: Llms and data pipelines for industrial multi-agent generative systems.

What are compound ai systems and ai agents? (2025). https://docs.databricks.com.

What is vertex ai agent builder? (2025). https://cloud.google.com/generative-ai-app-builder/docs/introduction.

Winston, A. (2024). What are ai agents and why do they matter?

wmwxwa (2024). Ai agents and solutions - azure cosmos db. https://learn.microsoft.com/en-us/azure/cosmos-db/ai-agents.

Yang, H., Zhang, B., Wang, N., Guo, C., Zhang, X., Lin, L., and Wang, C. D. (2024). Finrobot: an open-source ai agent platform for financial applications using large language models. *arXiv preprint*, arXiv:2405.14767.

Yee, L., Chui, M., Roberts, R., and Xu, S. (2024). Why agents are the next frontier of generative ai. Technical report, McKinsey Digital Practice.

Yu, Y., Yao, Z., Li, H., Deng, Z., Cao, Y., Chen, Z., Suchow, J. W., Liu, R., Cui, Z., Xu, Z., et al. (2024). Fincon: A synthesized ilm multi-agent system with conceptual verbal reinforcement for enhanced financial decision making. *arXiv preprint*, arXiv:2407.06567.

Zhang, W., Zhao, L., Xia, H., Sun, S., Sun, J., Qin, M., Li, X., Zhao, Y., Cai, X., et al. (2024). A multimodal foundation agent for financial trading: Tool-augmented, diversified, and generalist. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 4314–4325.

APPENDICES

Table 1. Application Areas of AI Agent Frameworks

Application Area	Key Contributions	Challenges	Future Directions
Financial Services ???	AI agents enhance investment analysis, risk assessment, fraud detection, and customer service automation. FinRobot and Fincon explore multi-agent financial decision-making.	Data privacy and explainability concerns. Limited adoption in real-time trading environments.	Development of explainable AI techniques. Integration of reinforcement learning for portfolio management.
Healthcare fsb (2024); Yee et al. (2024)	AI agents support drug discovery, patient monitoring, and personalized treatment recommendations. Multi-agent models improve diagnostics and decision support.	Ethical concerns around AI decision-making in medical applications. Need for regulatory compliance.	Federated learning to enhance privacy. AI-human collaborative decision-making for healthcare.
Autonomous Systems	AI agents improve robotics, self-driving vehicles, and smart city applications. Multi-agent reinforcement learning optimizes coordination.	Safety and reliability in real-world scenarios. Complex multi-agent interactions increase unpredictability.	More robust reinforcement learning frameworks. AI-driven simulations for real-world training.
Enterprise AI crickman (2025); pwc (2024)	AI agents automate business processes, improve customer service, and enhance decision-making. Enterprise applications integrate AI copilots.	High computational costs. Customization challenges for different industries.	Scalable cloud-based agentic AI frameworks. Standardization of agent-based enterprise solutions.
Cybersecurity Clatterbuck et al. (2024); See (2024)	AI agents detect and mitigate cyber threats, analyze vulnerabilities, and automate security operations.	Evasion techniques used by adversaries against AI-based security systems. Explainability in cybersecurity decision-making.	Adversarial training to improve robustness. AI-driven threat intelligence systems.

Table 2. Comparison of AI Agent Applications in Finance. Captions will always be left-aligned and in italics in the final version of the professionally formatted chapter

Application Area	Description	Relevant References
Investment Analysis	AI agents analyze financial data to identify opportunities and provide insights to portfolio managers.	Han et al. (2024), Zhang et al. (2024), Microfoundations et al. (2024)
Risk Management	AI agents assess and manage financial risks by analyzing market trends and identifying threats.	Clatterbuck et al. (2024), wmwxwa (2024), See (2024)
Fraud Detection	AI agents detect fraudulent activities by analyzing transaction patterns and identifying suspicious behavior.	dat (2025) (Implied - fraud detection is a common use case)
Customer Service	AI-powered virtual assistants provide personalized customer service and support.	N/A
Algorithmic Trading	AI agents develop and execute automated trading strategies.	Zhang et al. (2024), Microfoundations et al. (2024)
Personalized Financial Advice	AI agents tailor financial advice to individual clients based on their needs and goals.	N/A
Regulatory Compliance	AI agents assist financial institutions in complying with regulations.	fsb (2024), See (2024)
Credit Scoring	AI agents improve credit scoring and loan approval processes.	N/A
Market Surveillance	AI agents monitor financial markets for manipulative behavior or unusual activity.	Microfoundations et al. (2024) (Implied - market models can be used for surveillance)
Portfolio Management	AI agents optimize and manage investment portfolios.	Han et al. (2024)

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Table 3. Distribution of References by Year. Captions will always be left-aligned and in italics in the final version of the professionally formatted chapter

Year	Number of References	Example References
2025	8	Arya (2025), Aydın (2025), crickman (2025), goo (2025), mit (2025), cam (2025)
2024	24	Clatterbuck et al. (2024), Han et al. (2024), Yang et al. (2024), Yu et al. (2024), Zhang et al. (2024), Winston (2024), fsb (2024), Yee et al. (2024), See (2024), Microfoundations et al. (2024), pwc (2024), Ian (2025a), cre (2025), pyd (2025), Crickman (2024), rel (2025), Amos (2024), hac (2024), dev (2024), bot (2025), Clatterbuck et al. (2024), van Schalkwyk (2024), dee (2025), wmwxwa (2024), dat (2025)
2023	1	moo (2023)
2007	1	Chen (2007)

The list of references represents a distribution of references by year in the context of AI and financial services.

Table 4. Comparison of Agentic AI Frameworks. Captions will always be left-aligned and in italics in the final version of the professionally formatted chapter

Framework	Limitations	Use Cases
LangChain lan (2025a)	Limited in handling multi-agent collaboration. Performance bottlenecks with large-scale tasks.	Conversational AI, automated research, and tool-based reasoning.
CrewAI cre (2025)	High overhead for managing multiple agents. Requires careful tuning for task delegation.	Workflow automation, AI-powered teams, autonomous research assistants.
Semantic Kernel crickman (2025)	Enterprise-focused, requiring significant customization. Limited adoption outside of Microsoft ecosystem.	AI copilots for business applications, enterprise AI integrations.
FinRobot ?	Limited generalization beyond financial applications. Requires domain-specific knowledge.	AI agents for financial risk analysis, portfolio management, trading automation.
Fincon ?	Requires large-scale training data. High computational cost for deployment.	AI-driven market analysis, automated trading bots, financial forecasting.
AutoGen dee (2025)	Steep learning curve for new users. Requires fine-tuning for specific tasks.	AI-powered document processing, task automation, research agents.
LlamaIndex wmwxwa (2024)	Not optimized for real-time agent interactions. Limited support for multi-agent collaboration.	AI-driven search and knowledge management, enterprise AI solutions.

Each framework provides different capabilities, with unique advantages and limitations for implementing AI agents in various domains.

Table 5. Research Gaps and Future Work in AI Agent Research. Captions will always be left-aligned and in italics in the final version of the professionally formatted chapter

Research Area	Research Gaps	Future Work
AI Agent Frameworks	Lack of standardized benchmarks for AI agent frameworks Arya (2025). Limited evaluation of real-world scalability Aydın (2025).	Develop standardized performance benchmarks Amos (2024). Explore hybrid AI-agent frameworks combining symbolic and neural approaches.
AI Agents in Finance	Limited real-world deployment studies in high-frequency trading Zhang et al. (2024). Explainability and regulatory compliance remain major concerns fsb (2024).	Conduct more empirical evaluations of AI agents in trading environments Microfoundations et al. (2024). Develop XAI (Explainable AI) frameworks to improve transparency in financial applications.
Challenges	Lack of robust methodologies for ensuring financial data quality See (2024). Insufficient research on adversarial robustness of AI agents in finance.	Investigate robust data cleaning and augmentation techniques moo (2023). Develop adversarial defense mechanisms for financial AI agents.
Future Directions	Limited research on the synergy between AI agents and reinforcement learning in finance. Lack of ethical and regulatory guidelines for AI-driven markets pwc (2024).	Explore reinforcement learning-based AI agent strategies for portfolio management wmwxwa (2024). Develop AI governance frameworks to address ethical concerns.

The table summarizes research gaps and potential future work in the field of AI agents across multiple domains.

Table 6. Comparison of AI Agent Applications in Finance. Captions will always be left-aligned and in italics in the final version of the professionally formatted chapter

Application Area	Description	Relevant References
Investment Analysis	AI agents analyze financial data to identify opportunities and provide insights to portfolio managers.	Han et al. (2024), Zhang et al. (2024), Microfoundations et al. (2024)
Risk Management	AI agents assess and manage financial risks by analyzing market trends and identifying threats.	Clatterbuck et al. (2024), wmwxwa (2024), See (2024)
Fraud Detection	AI agents detect fraudulent activities by analyzing transaction patterns and identifying suspicious behavior.	dat (2025) (Implied - fraud detection is a common use case)
Customer Service	AI-powered virtual assistants provide personalized customer service and support.	N/A
Algorithmic Trading	AI agents develop and execute automated trading strategies.	Zhang et al. (2024), Microfoundations et al. (2024)
Personalized Financial Advice	AI agents tailor financial advice to individual clients based on their needs and goals.	N/A
Regulatory Compliance	AI agents assist financial institutions in complying with regu lations.	fsb (2024), See (2024)
Credit Scoring	AI agents improve credit scoring and loan approval processes.	N/A
Market Surveillance	AI agents monitor financial markets for manipulative behavior or unusual activity.	Microfoundations et al. (2024) (Implied - market models can be used for surveillance)
Portfolio Management	AI agents optimize and manage investment portfolios.	Han et al. (2024)

Each framework contributes differently to the development of AI agents and their capabilities. The references include both foundational papers and implementations.

Table 7. Distribution of Cited Literature by Publication Year

Year	Count	Representative Works
2025	10	Joshi (2025d), Joshi (2025q), Joshi (2025k), Joshi (2025o)
2024	20	Han et al. (2024), Microfoundations et al. (2024), Yang et al. (2024), Yu et al. (2024), Zhang et al. (2024), Winston (2024), fsb (2024), Yee et al. (2024), Clatterbuck et al. (2024), See (2024)
2023	2	moo (2023)
Pre-2023	1	Chen (2007)

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