A Comprehensive Review of Gen AI Agents: Applications and Frameworks in Finance, Investments and Risk Domains

(Current State and Future of Gen AI Agents)

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Abstract: This paper surveys the landscape of AI agent frameworks, highlights their core features and differences, and explores their applications in financial services. We synthesize insights from recent industry reports, academic research, and technical blog posts, focusing on frameworks such as CrewAI, LangGraph, LlamaIndex, and others. We also discuss the challenges and opportunities of deploying agentic AI in production environments, with an emphasis on financial trading, investment analysis, and decision support. We analyze the rapidly evolving landscape of agentic AI systems, focusing on their architecture, capabilities, and practical implementations in banking, trading, and risk management. The study examines prominent frameworks including LangGraph for stateful agent orchestration, CrewAI for collaborative multi-agent workflows, and AutoGen for conversational agent systems, alongside industry platforms like IBM watsonx and NVIDIA NIM. The study examines both technical frameworks (LangGraph, CrewAI, AutoGen, etc.) and practical implementations in financial institutions. We highlight productivity gains (up to 80% time reduction in data tasks), risk management improvements, and workforce transformation challenges. The paper concludes with recommendations for financial institutions adopting agentic AI solutions. Our analysis reveals three key findings: (1) specialized agent frameworks achieve 50-80% productivity gains in financial data tasks compared to traditional approaches, (2) multi-agent systems demonstrate particular promise in complex domains like algorithmic trading and fraud detection, and (3) successful deployment requires addressing critical challenges in workforce upskilling, risk alignment, and regulatory compliance. The paper provides a theoretical foundation for agentic AI in finance, introducing formal models for agent design patterns, multimodal fusion, and market microfoundations. We further present a summary of several evaluation frameworks for assessing agent performance across financial use cases, including portfolio optimization and AML compliance. The study concludes with recommendations for financial institutions adopting agentic AI, emphasizing the need for standardized architectures, robust testing protocols, and hybrid human-AI workflows.

Keywords: *AI Agents, Agentic AI, Financial Services, Multi-Agent Systems, Generative AI, Risk Management, Multi-Agent Systems, Financial Technology, LLMs Autonomous Agents, Frameworks.*

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I. INTRODUCTION

Agentic AI, or AI systems that can independently reason and act in multiple steps, is the new era of artificial intelligence. Large Language Models (LLMs) allow agents to reason, plan, and interact with complex environments, thereby allowing different types of enterprise and industrial applications. In the financial industry, there is the agentic AI being investigated for trading and analysis of investment, compliance, and workflow automation.

The financial services industry is being undergoing radical changes in its transformation with the usage of AI agent frameworks. Latest trends in 2024-2025 indicate tremendous achievements in both frameworks of agents and their financial implementations.

However, a number of key aspects need to be worked out in future work:

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- *Scalability:*

Testing the scalability of the architecture to be able to process a great amount of agents and complicated financial cases.

- *Real-Time Performance:*

Evaluating the system to work at real time and make prompt decisions in ever changing market environment.

- *Regulatory Compliance:*

Ensuring that the system complies with relevant financial regulations and ethical guidelines.

- *Integration with Existing Systems:*

Exploring how the architecture can be integrated with existing financial systems and infrastructure.

As noted by [1], generative AI is becoming a utility similar to electricity, with multi-agent systems emerging as the next evolutionary step.

- *Gen AI Agents in Finance*

Coming together of multi-agent systems and artificial intelligence has a long history and the earliest research therein concentrated in such areas as distributed problem-solving, cooperative robotics, game theory. Chen [2] paved the way for using computationally intelligent agents in economics and finance as his works confirmed that they are capable of simulating complicated behaviors of markets and agent interrelations.

The introduction of Large Language Models (LLMs) has radically changed the AI sphere, which allowed to create more intelligent and autonomous agents. According to Pounds [3] and Jadhav [4], agentic AI implies a paradigm shift towards self-reasoning, self-planning, and self-acting AI systems that increase MAS capabilities many fold. Winston [5] underscores the necessity to understand AI agents and the increasing effect.

Several platforms and frameworks have emerged to facilitate the development of AI agents. LangChain [6] provides a versatile toolkit for building agents that can interact with external data sources and tools. LangGraph [7] offers a lower-level abstraction for building stateful and interactive agentic applications. CrewAI [8] focuses on orchestrating collaborative multi-agent workflows. AutoGen [9] simplifies the creation of multi-agent conversations. Sir, other notable frameworks include Semantic Kernel [10], Agent force [11], Mosaic AI Agent Framework [12], [13], and the cloud platforms like the Google Cloud's Vertex AI Agent builder [14] the amazon Bedrock agent [15], the azure Cosmos DB [16] and the IBM watson Pydantic-AI [18], [19] offer tools for incorporating the usage of Pydantic in conjunction with LLMs when developing agents.

Comparative analyses of these frameworks, for instance, by Aydın [20], Relari AI [21], and others [22], provide useful insights into the strengths, weaknesses and applicability of each of them for different purposes.

The use of AI agents in the financial sphere is an emerging sphere. Reports [23] from McKinsey and [24] the World Economic Forum indicate the potential transformative power of the machine agentic AI in transforming the financial services. Examples are AI traders in the financial market [25], [26], LLM-based multi-agent systems for financial decision-making [27, 28], and open-source AI agent platforms for financial use [28]. Some of the research on AI agents is also centered on better investment analysis [29] and improved productivity of employees in financial institutions [30], [31]. Other companies such as Cognizant are building AI solutions for the financial industry.

However, the adoption of AI agents in finance would also cause grave concerns. Risk management is fundamental [33], [34], [35], [36], and making the appropriate and ethical uses of AI is pivotal [37], [38]. The Financial Stability Board [39] and other central banks such as the European Central Bank [40] are vigorously pursuing the possible dangers of AI in the domain of financial services. Moody's Analytics has further looked at the emergence of AI agents in finance [41], [42]. International Banker also touches on the balancing of risk and transformation of workforce [43].

AI agents are transforming the financial sector through their capacity to address complex challenges including risk management, fraud detection, investment strategies, and customer engagement. This scholarly review categorizes contemporary research, highlighting quantitative outcomes, identifying research lacunae, and suggesting future trajectories. The significant impact of AI agents on the financial landscape stems from their application to intricate problems across multiple domains of finance. This analysis provides a systematic classification and evaluation of current studies to deliver insights regarding practical implementations and measurable results [41], [44].

The ongoing influence of AI agents in financial contexts manifests through their application to challenging issues across various financial operations. This review systematically organizes and synthesizes recent literature to provide perspectives on practical applications and quantitative metrics. The progressive transformation of financial environments through AI agents continues as they address multifaceted challenges in financial management and customer relations. This scholarly assessment classifies and evaluates contemporary research to elucidate practical applications and empirical outcomes [33], [41], [44], [45], [46], [47].

AI agents represent a pivotal development reconfiguring the financial domain through their capability to resolve sophisticated tasks across financial operations. This analysis categorizes and condenses recent scholarly work to offer perspectives on practical implementations and quantitative impacts [33], [41], [44], [45], [46]. The financial sector's evolution continues through AI agent applications that address complex financial challenges. This structured review evaluates modern research to determine practical applications and measurable results.

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The corresponding reference [41] addresses the expanding influence of AI within financial services, while [44] examines the associated challenges and risks to the finance sector. The Financial Stability Board discusses AI and ML applications in financial services in [39], and [48] analyzes AI's impact on regulatory documentation. Reference [49] outlines methodologies for financial institutions to optimize value and mitigate risks through generative AI implementation, whereas [45] presents agentic AI as an emerging frontier. Reference [35] examines AI and generative AI contributions to credit risk management advancement, while [50] argues for the significance of synthetic data over generative AI. The perspective that agents represent generative AI's next frontier is articulated in [23], with [33] focusing on risk alignment issues in agentic AI systems. Reference [46] examines generative AI's sectoral impacts, and [51] provides payment systems analysis. In scholarly literature, [52] concentrates on computationally intelligent financial agents, while [53] introduces the FinVision multi-agent framework for stock market prediction. Reference [54] enhances AI-agent collaboration in financial research, and [55] examines AI traders' market influence. FinRobot, an open-source AI agent platform for financial applications, is presented in [56], while [57] introduces Fincon, a synthesized LLM multi-agent system for enhanced financial decision-making. Reference [47] proposes a multimodal foundation agent for financial trading, building upon Josih's previous research [82-96].

- *Overview of Modern AI Agent Frameworks*

A variety of frameworks have emerged to support the development and deployment of AI agents. These range from open-source libraries to enterprise-grade platforms.

✓ *General-Purpose Frameworks*

LangGraph is a low-level orchestration framework for building controllable agents with state management and debugging tools [7]. CrewAI specializes in collaborative, role-based agent teams [8]. LlamaIndex (llama-agents) focuses on connecting LLMs to enterprise data for knowledge-intensive applications [58]. Other notable frameworks include PydanticAI [18], [19], Semantic Kernel [10], and AutoGen [9].

✓ *Industry and Cloud Solutions*

Major cloud providers and enterprises vendors have announced agentic AI platforms, including NVIDIA NIM [59], IBM watsonx [17], [60], Amazon Bedrock Agents [15], and Salesforce Agentforce [11]. These platforms have business APIs integration capabilities, scalability and compliance capabilities as well.

II. AI AGENT FRAMEWORKS: A COMPARATIVE ANALYSIS

Behind the success of the effective multi-agent systems are the AI agent frameworks. This part makes representative comparative analysis of some of the most prominent frameworks, whereby their major characteristics, strong and weak points are presented.

- *LangChain*

LangChain [6] is a flexible framework, which makes it easier to integrate LLMs with external data sources and tools. Its modular architecture makes it possible for developers to develop agents with a wide range of capabilities ranging from information retrieval tasks, code execution, and web browsing. The strength of LangChain is its adaptability and big ecosystem of integrations.

- *LangGraph*

LangGraph [7] gives a more low-level abstraction for developing stateful interactive agentic applications. It allows establishing complex workflows of agents with a clearly defined control of interactions and state transitions between the agents. LangGraph is especially valuable for applications that need a fine-grained control over an agent's behavior.

- *CrewAI*

CrewAI [8] pays more attention to the orchestration of multiparty agent's workflows. It enables developers to create agents that have certain roles and responsibilities and synchronize their communications to perform complex tasks. CrewAI is appropriate for applications that require collaboration and division of the tasks among agents.

- *AutoGen*

AutoGen [9] makes it easy for one to design multi-agent conversations. It allows to build agents that are able to communicate with each other in order to find joint solutions to the problems. AutoGen is especially effective for creating conversational AI systems and applications that have complex reasonings and debates.

- *Other Frameworks*

Other frameworks include Semantic Kernel [10] which focuses on combining semantic functions with LLMs, and cloud service's platforms like Google cloud's Vertex AI Agent Builder [14] and Amazon Bedrock Agents [15] which offer tools for building and deploying agents within their own cloud ecosystem. IBM watsonx.ai [17] provides features for agent development as well. Agentforce [11] and Mosaic AI Agent Framework [12] are also mentionable.

- *Comparison and Suitability for Finance*

An appropriate agent framework is chosen based on the required needs of a financial application. For instance, the flexibility of LangChain could be adequate for implementing agents that have to access different sources of financial data while CrewAI could be useful as a tool for developing systems that use teams of agents for performing various workers of analytical tasks. Sophisticated financial forecasting may be done through AutoGen. Specifical scalability, robustness and explainability, availability of certain financial tools and libraries should also be taken into account.

III. PROPOSED MULTI-AGENT ARCHITECTURE

Here, we describe our new multi-agent architecture for sophisticated financial analysis. Our architecture makes use of the strengths of LLMs.

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- *Architecture Overview*

Our architecture comprises three key layers:

✓ *Data Layer:*

This layer is in charge of collection, storage and management of the financial data from various sources. It has elements for data acquisition, preprocessing and storage. Technologies such as Retrieval Augmented Generation (RAG) [61] can for example be used to make the agent better equipped to draw on and use information from this layer. The information pipelines with LLMs and multi-agent systems are considered in [1].

✓ *Agent Layer:*

The layer is comprised of a set of intelligent agents which are specialized in a particular financial process. Agents in this layer are driven by LLMs and have reasoning, planning, communication, action execution abilities.

✓ *Orchestration Layer:*

This layer is charged with coordinating activities of agents within the Agent Layer. It provides management of agents communication, task allocation, conflict resolution and system behavior altogether. One can gain helpful impressions on designing successful communication protocols using frames such as Camel [62], such as.

- *Agent Design*

Each agent in the Agent Layer is designed with the following components:

✓ *LLM-Powered Cognition Module:*

This module makes use of a pre-trained LLM being fine-tuned for financial data, to carry out functions like data analysis, forecasting, risk assessment, and so forth.

✓ *Domain Knowledge Base:*

This module keeps domain information, such as financial concepts, market regulations, and information about companies.

✓ *Communication Interface:*

Such a module allows the agents to communicate with each other and with the Orchestration Layer in the form of a standardized message.

✓ *Action Execution Engine:*

This module carries out the functions devised by the agent's cognition module, among which are retrieval of data, carrying out calculations, and producing reports. Pydantic [19] may be used to guarantee data integrity.

- *Orchestration Mechanisms*

The Orchestration Layer employs a combination of techniques to manage agent interactions:

✓ *Task Decomposition:*

Complex financial tasks are broken down into simple sub tasks that can be allocated from one agent.

✓ *Agent Negotiation:*

Agents communicate with one another so as to establish the most effective ways of accomplishing their required tasks.

✓ *Conflict Resolution:*

There are mechanisms to solve the conflict that may crop up between agents.

✓ *System Monitoring:*

The Orchestration Layer ensures the entire system performances are monitored and intervention is made in due time.

IV. EVALUATION STRATEGY

To rigorously evaluate the effectiveness of our proposed multi-agent architecture, we define a comprehensive evaluation strategy.

- *Evaluation Scenarios*

We will evaluate our architecture in the following financial scenarios:

✓ *Portfolio Optimization:*

Agents will work together to serve optimum investment portfolios according to risk tolerance, returns, and market conditions.

✓ *Fraud Detection:*

Agents will analyze the data on transactions in order to identify the patterns that show fraudulent activity. Agents that are AI are being created to battle financial crime [63].

✓ *Algorithmic Trading:*

Agents will come up with and implement trading strategies within a virtual environment [25].

✓ *Financial News Analysis:*

Agents will analyze news articles and social media data to identify market trends and sentiment.

- *Evaluation Metrics*

We will evaluate the performance of our architecture using the following key performance indicators (KPIs):

✓ **Accuracy**: The accuracy of agent predictions and decisions in each scenario.
✓ **Efficiency**: The speed and resource consumption of the system in completing tasks.
✓ **Robustness**: The ability of the system to handle noisy or incomplete data and unexpected events.
✓ **Explainability**: The degree to which agent decisions can be explained and justified.
✓ **Risk-Adjusted Return**: A measure of investment performance that considers the level of risk taken.

- *Benchmarking and Baselines*

We will compare the performance of our architecture against the following baseline methods:

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- ✓ **Baseline 1**: A traditional rule-based system that uses predefined rules to perform financial analysis.
- ✓ **Baseline 2**: A single-agent system that utilizes an LLM but does not involve multi-agent coordination.
- ✓ **Baseline 3**: Existing state-of-the-art financial models (where applicable to the scenario).

V. AGENTIC AI IN FINANCE

The finance sector is at the forefront of adopting agentic AI due to its need for automation, data analysis, and risk management.

- *Risk Management*

Agentic AI shows particular promise in financial risk:

- ✓ 45% of firms now use GenAI for risk management [34]
- ✓ Credit risk analysis improvements through agent collaboration [35]
- ✓ Automated AML/KYC processes via specialized agents [63]

- *Trading and Investment*

Multi-agent systems are transforming trading:

- ✓ [25] demonstrate AI trader impact on markets
- ✓ FinRobot [28] provides open-source platform for financial LLMs
- ✓ Multimodal agents combine diverse data sources [26]

- *Productivity Enhancements*

- ✓ Capitec Bank reports 1+ hour weekly savings per employee [64]
- ✓ West Monroe’s agent reduces data task time by 80% [65]
- ✓ JPMorgan’s AI assistant improves operations [66]

- *Customer Experience*

- ✓ Interface.ai’s agentic copilot boosts efficiency [30]
- ✓ Zetaris introduces specialized agents for financial services [67]
- ✓ Retrieval-Augmented Generation (RAG) enhances banking services [61]

- *Financial Trading and Investment*

Researchers have demonstrated the use of multi-agent systems for market modeling and trading [25], [26], [28]. For example, FinRobot is an open-source agent platform for financial applications using LLMs [28]. Multimodal agents can leverage diverse data sources, tools, and reasoning strategies to optimize trading decisions [26]. Enhanced agent collaboration has been shown to improve investment analysis and financial research outcomes [29].

- *Decision Support and Workflow Automation*

Agentic AI frameworks are being used to automate data pipelines, compliance checks, and customer support in banking and fintech [1], [17], [60], [68]. Synthesized multi-agent systems can enhance financial decision-making through conceptual reinforcement and collaborative reasoning [27].

- *Technical and Safety Considerations*

As agentic systems become more autonomous, documenting their technical and safety features is essential [69]. Frameworks like LangGraph and CrewAI offer debugging and state management tools to address these needs [7], [8].

VI. AI AGENT FRAMEWORK LANDSCAPE

The AI agent ecosystem has exploded with numerous frameworks offering distinct capabilities:

- *General Purpose Frameworks*

- ✓ **LangGraph**: A low-level orchestration framework from LangChain enabling controllable agents with state management [7]
- ✓ **CrewAI**: Specializes in role-based agent collaboration with built-in task delegation [8]
- ✓ **AutoGen**: Microsoft’s framework for building multi-agent systems with diverse capabilities [9]
- ✓ **Llama-agents**: LlamaIndex’s production-ready framework for enterprise knowledge systems [58]
- ✓ **Semantic Kernel**: Microsoft’s experimental agent framework integrating with AI services [10]

- *Industry-Specific Solutions*

Financial institutions are adopting specialized platforms:

- ✓ NVIDIA NIM for generative AI deployment [59]
- ✓ IBM watsonx.ai for enterprise-grade AI development [60]
- ✓ Salesforce Agentforce for CRM automation [11]
- ✓ AWS Bedrock Agents for business task automation [15]

Recent comparative studies [21], [70], [71] highlight the strengths of different frameworks. [72] identifies seven top frameworks for 2025, while [73] focuses on multi-agent applications. The Pydantic-AI framework [19] offers unique integration with Python type systems.

VII. CLOUD PYTHON LIBRARIES FOR AI AGENT DEVELOPMENT

Cloud-native libraries of Python are key to the fast development and deployment of agentic AI solutions in finance. These libraries allow scalable and distributed production-ready workflow in a production environment, both for experimentation and enterprise use. Thanks to cloud-based Python libraries, the AI agents development for financial services has been greatly speeded up as such libraries allow creating scalable infrastructure and have available ready-made components. These libraries allow for fast deployment of agentic systems without having to deal with the complexities of distributed computing and cloud integration.

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The cloud computing platforms offer a vast variety of Python libraries, which make the development and deployment of AI agents easier. These libraries provide a range of functions ranging from data storage, retrieval, training, and deployment of models. Here are some notable examples:

✓ *Google Cloud Libraries:*

Google Cloud has libraries such as Vertex AI that comes with tools on how to build, deploy, and scale machine learning (ML) models. Using Vertex AI Agent Builder [14], it is possible to design virtual AI agents.

✓ *Amazon Web Services (AWS) Libraries:*

AWS provides services like Amazon Bedrock, and Bedrock Agents [15] which enables the building of generative AI applications.

✓ *Microsoft Azure Libraries:*

Microsoft Azure offers Azure Cosmos DB [16], a database service that can be used to build AI agent memory systems. Additionally, Microsoft's Semantic Kernel [10] can be used in conjunction with Azure services.

✓ *IBM Cloud Libraries:*

IBM Cloud provides watsonx.ai [17], [60], a platform with tools for the AI development lifecycle.

These cloud-based Python libraries provide developers with the necessary tools to build and deploy scalable and robust AI agent systems.

- *Major Cloud Python Libraries*

✓ *LangChain/LangGraph:*

Provides comprehensive tools for building LLM-powered agents with cloud deployment capabilities [7]. The framework supports AWS, GCP, and Azure integration for scalable agent systems.

✓ *Pydantic-AI:*

Offers cloud-optimized agent development with strong typing and validation, particularly useful for financial data pipelines [19]. The library includes connectors for major cloud platforms.

✓ *IBM watsonx:*

Delivers enterprise-grade AI agents with native cloud support through Python SDKs [60]. The platform specializes in secure financial applications with built-in compliance features.

✓ *Mosaic AI Agent Framework:*

Databricks' solution for building autonomous AI assistants with cloud-native architecture [12]. It integrates seamlessly with Databricks' Lakehouse platform for financial data processing.

- *Cloud-Specific Implementations*

Table 1 summarizes key AI agent libraries across major cloud platforms.

Table 1 Cloud Libraries

Cloud Platform	Library	Key Feature
AWS	Bedrock Agents	API integration for financial systems [15]
Azure	Semantic Kernel	.NET/Python hybrid agents [10]
GCP	Vertex AI Agent Builder	Financial recommendation systems [14]
Multi-cloud	Camel-AI	Multi-agent coordination [62]

- *Financial Services Specialization*

Recent advancements in cloud Python libraries specifically target financial applications:

✓ **FinRobot** [28]: Open-source platform with cloud connectors for market data feeds and trading APIs.
✓ **Zetaris Agentic AI** [67]: Cloud-native solution for financial data virtualization and agent-based analytics.
✓ **WorkFusion AI Agents** [63]: Specialized cloud library for anti-financial crime applications with pre-built AML/KYC workflows.

- *Performance Considerations*

Cloud-based agent systems demonstrate significant performance advantages:

✓ **Scalability**: Multi-agent systems like those built with [8] can automatically scale across cloud regions during market hours.
✓ **Latency**: Frameworks such as [21] optimize cloud deployment for low-latency trading applications.
✓ **Cost Efficiency**: [72] reports cloud-based agents can reduce infrastructure costs by 30-40% compared to on-premise solutions for equivalent workloads.

The evolution of these cloud Python libraries has lowered the barrier to entry for financial institutions adopting agentic AI, while providing the security and compliance features required in regulated environments [45].

- *Agno: Cloud-Native Agent Framework*

Agno is a Python framework designed for building and deploying LLM-powered agents in the cloud, with features for multi-agent orchestration, cloud deployment, and integration with major providers such as AWS [73]. Agno supports both local and cloud workflows, offering a built-in agent UI, session management, and monitoring tools. Its modular design allows users to connect to models from OpenAI, Anthropic, Cohere, and more, making it suitable for both research and production environments.

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- *Best Practices for Cloud Python Environments*

When deploying agentic systems in the cloud, it is recommended to use isolated Python environments, such as venv, to manage dependencies and ensure reproducibility. Agno provides templates and pre-configured codebases to accelerate the transition from prototype to production, with support for monitoring and debugging in distributed cloud settings.

- *Alternative Libraries and Approaches*

Several other frameworks and libraries also support cloud-based agentic workflows. For example, the PydanticAI project demonstrates how Python type systems can be leveraged for agent orchestration, and offers cloud deployment options [18]. Additionally, the open-source ecosystem continues to expand, with projects like CrewAI and LlamaIndex providing modular, cloud-compatible solutions for multi-agent systems and enterprise data integration [8], [58].

- *Summary*

The trend in cloud Python libraries is toward modularity, composability, and seamless integration with cloud infrastructure. Frameworks like Agno and CrewAI exemplify these principles, enabling the rapid development and deployment of robust agentic AI systems in finance and beyond [8].

VIII. THEORETICAL FOUNDATIONS OF AGENTIC AI

➢ *Based on the Surveyed Literature, we Identify Ten Core Theoretical Concepts that Underpin Modern Agentic AI Systems:*

- **Agentic Design Patterns -** Architectural templates for creating autonomous agents capable of iterative planning and tool use [3]. Characterized by:

$$A = (S, \Pi, M, T)$$

Where

S=states, Π =policies, M =memory, T =tools.

- **Multi-Agent Scaling Laws -** Quantitative relationships between agent count and system performance [62]. Demonstrated through:

$$P(n) \sim n^{\alpha} \log(n)$$

Where

α is task-dependent.

- **Verbal Reinforcement Learning -** Conceptual reinforcement through language feedback rather than numeric rewards [27]. Formalized as:

$$\pi_{t+1} = \pi_t + \eta \nabla E\left[f_{\text{lang}}(R)\right]$$

- **Financial Market Microfoundations -** Agent-based models explaining macro phenomena through individual agent behaviors [25]. Price formation follows:

$$p_{t+1} = p_t + \sum_i w_i a_i(p_t, x_i)$$

- **Multimodal Fusion Theory -** Framework for combining diverse financial data modalities [26]. Uses attention mechanisms:

$$h = \text{softmax}\left(QK^T / \sqrt{d}\right)V$$

- **Agentic Workflow Optimization -** Mathematical formulation of task decomposition in financial processes [29]. Minimizes:

$$L = \sum_{k=1}^{K} \| T_k - \bigcup_i \pi_i^k \|^2$$

- **Conceptual Alignment -** Ensuring agent reasoning aligns with financial domain concepts [27]. Measured by:

$$A = E\left[\text{sim}(c_{\text{human}}, c_{\text{agent}})\right]$$

- **Risk-Aware Learning -** Adaptation mechanisms considering financial risk constraints [35]. Policies satisfy:

$$\pi \in \{\pi' \vee P(r_{\text{risk}} > \theta) < \epsilon\}$$

- **Computational Principal-Agent Theory -** Formalizing delegation in AI-human teams [2]. Models:

$$\max_{a \in A} u_p(a) \text{ s.t. } a \in \arg\max_{a'} u_a(a')$$

- **Generative Economic Equilibrium -** Stable states in AI-augmented financial systems [25]. Requires:

$$\forall i, \pi_i^{¿} \in \text{BR}(\pi_{-i}^{¿})$$

Where BR denotes best response.

These theoretical constructs provide the mathematical foundation for current agentic AI systems in finance, spanning individual agent design to market-scale interactions. The field continues to evolve through formalization of these concepts [39], [45].

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IX. MULTI-AGENT SYSTEM ARCHITECTURES

➢ *Microfoundations Market Model*

[25] proposes a multi-agent market simulation framework where each agent $a_i \in A$ is modeled as:

$$a_i = (s_i, \pi_i, \theta_i)$$

Where:

- s_i : Agent state (e.g., portfolio, risk tolerance),
- π_i : Policy function, $\pi_i : O \to A$,
- θ_i : Learning parameters.

The market evolves in discrete time steps with price formation governed by:

$$p_t = f\left(\sum_{i=1}^{N} w_i \cdot \pi_i(o_t)\right) + \epsilon_t$$

Where w_i denotes trading volume weights and ϵ_t is market noise.

➢ *FinCon Architecture*

[27] introduces a multi-LLM architecture employing verbal reinforcement for reasoning refinement, formalized as:

Input: Transaction T
$\text{Alert} \leftarrow \text{TransactionMonitoring}(T)$
$\text{RiskScore} \leftarrow NN_{AML}(\text{Alert})$
$\text{Investigation} \leftarrow \text{MultiAgentReview}(\text{Alert})$
$\text{Decision} \leftarrow \text{EnsembleVote}(\text{Investigation})$
$\text{Decision} \leftarrow \text{NoAction}()$ **Output:** Decision

➢ *Specialized Trading Architectures*

- *Multimodal Foundation Agent*

[26] proposes a tool-augmented trading agent with multimodal feature fusion:

$$\hat{a}_t = \text{softmax}\left(W_\phi \cdot \left[f_{\text{text}}(x_t); f_{\text{chart}}(y_t); f_{\text{news}}(z_t)\right]\right)$$

Where:

- ✓ f_{text}: Textual data encoder,
- ✓ f_{chart}: Technical analysis encoder,
- ✓ f_{news}: News sentiment encoder,
- ✓ W_ϕ: Learnable fusion weights.

- *FinRobot Platform*

[28] introduces a modular, layered architecture:

$$F = L_{\text{data}} \oplus L_{\text{LLM}} \oplus L_{\text{agent}} \oplus L_{\text{app}}$$

With each layer defined as:

- ✓ Data Layer L_{data} : $\{\text{market}, \text{fundamental}, \text{alternative}\}$,
- ✓ LLM Layer L_{LLM} : $\{\text{general}, \text{financial-finetuned}\}$,
- ✓ Agent Layer L_{agent} : $\{\text{single}, \text{multi}, \text{hybrid}\}$.

➢ *Risk Management Architectures*

- *Agentic AI for Credit Risk*

[35] proposes a hierarchical model for credit risk evaluation:

$$R(x) = g\left(\sum_{j=1}^{k} \alpha_j h_j(x)\right)$$

Where:

- ✓ h_j: Specialist risk sub-models (e.g., market, credit, operational),
- ✓ α_j : Attention weights derived from agent interactions,
- ✓ g: Final risk scoring function.

- *AML Agent Architecture*

The WorkFusion system [63] implements an AML pipeline using agent collaboration:

Input: Transaction T
$\text{Alert} \leftarrow \text{TransactionMonitoring}(T)$
$\text{RiskScore} \leftarrow NN_{AML}(\text{Alert})$
$\text{Investigation} \leftarrow \text{MultiAgentReview}(\text{Alert})$
$\text{Decision} \leftarrow \text{EnsembleVote}(\text{Investigation})$
$\text{Decision} \leftarrow \text{NoAction}()$ **Output:** Decision

➢ *Architectural Comparisons*

Cloud computing platforms provide diverse Python libraries for developing AI agents, as summarized in Table 2.

Table 2 Arc Comparison

Paper	**Type**	**Key Innovation**	**Math Foundation**
[25]	Market Sim	Agent-based price formation	Game Theory
[27]	Multi-LLM	Verbal reinforcement loop	Ensemble Learning
[26]	Trading	Multimodal fusion	Attention Mechanisms
[35]	Risk	Hierarchical scoring	Neural Networks

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X. PROPOSED ARCHITECTURES: MATHEMATICAL AND ALGORITHMIC FOUNDATIONS

Recent literature introduces a variety of architectures for agentic AI, each with unique mathematical and algorithmic principles.

➢ *Agent-Native and Modular Architectures*

Agent-native foundation models are designed for multi-step planning, dynamic tool use, and memory integration [3], [4], [5]. These models enable agents to adaptively allocate computational resources, which can be expressed as:

$$y = f(x; \theta, A)$$

where x is the input, θ are model parameters, and A represents agentic actions or tools invoked during reasoning [3].

➢ *Meta-Agent and Hierarchical Planning*

Meta-agent architectures introduce a supervisory agent that coordinates specialized sub-agents, optimizing for global objectives. This can be formalized as a hierarchical optimization problem:

$$\min_{\{\pi_i\}} \sum_{i=1}^{N} C_i(\pi_i) \text{ s.t. } \bigcup_{i=1}^{N} \pi_i \in G$$

where π_i is the plan for agent i, C_i is its cost, and G is the set of global goals.

➢ *Learning Agents and Reinforcement Learning*

Learning agents adapt their behavior through feedback, often using reinforcement learning (RL) or RL from human feedback. The RL objective is:

$$\pi^{¿} = \arg\max_{\pi} E\left[\sum_{t=0}^{T} \gamma^t r_t \,/\, \pi\right]$$

where π is the policy, r_t the reward at time t, and γ the discount factor.

➢ *Automated Agent Design*

Automated agent design leverages evolutionary algorithms to search the space of agent architectures. The process is:

$$\theta^{¿} = \arg\max_{\theta} F(\theta)$$

where θ encodes an agent architecture and F is a fitness function measuring performance.

➢ *Multi-Agent Coordination*

Multi-agent systems distribute tasks and coordinate via protocols such as negotiation or centralized planning. The coordination can be modeled as:

$$\min_{\{\pi_k\}} \sum_{k=1}^{K} C_k(\pi_k) \text{ s.t. } \mathrm{Coord}(\{\pi_k\}) = \mathrm{True}$$

where each agent's plan π_k must be compatible with others.

➢ *Algorithmic Example: Hierarchical Agent Planning*

A recursive algorithm for hierarchical agent planning is described:

Execute(goal) subgoals $\leftarrow$ Decompose(goal) result $\leftarrow$ Aggregate(results)

➢ *Summary*

The agentic AI field is evolving from monolithic LLMs to modular, hierarchical, and learning-enabled architectures, grounded in formal mathematical and algorithmic principles [3], [4], [5].

XI. FINANCIAL AGENTS

➢ *Financial Risk Agents*

AI agents in the financial risk domain predominantly focus on strengthening credit risk management, ensuring regulatory compliance, and improving operational risk assessment. Research by [41] emphasized generative AI agents' contribution to optimizing credit evaluation workflows. An analysis by [39] examined AI integration within financial risk management structures, documenting a 25% enhancement in risk model precision. Correspondingly, [49] stressed the importance of risk minimization alongside value maximization through generative AI implementations, resulting in an approximate 30% decrease in operational inefficiencies.

The quantitative outcomes from these significant investigations are consolidated in Tables 4 and 5, with the latter also addressing research gaps and prospective developments in this field.

Table 3 Summary of Financial Risk Agentic Models and Key Findings

Paper	Model/Approach	Key Findings
[41]	Generative AI for credit evaluation	20% reduction in loan default rates
[39]	AI risk management frameworks	25% improvement in risk model accuracy
[49]	Generative AI for operational risk	30% reduction in operational inefficiencies

Table 4 Models, Findings, Gaps and Future Work

Paper	Model/Approach	Key Findings	Gaps	Future Work
[41]	Generative AI for credit evaluation	20% reduction in loan default rates	Limited explainability of models	Develop interpretable AI models for credit scoring
[39]	AI risk management frameworks	25% improvement in risk model accuracy	Insufficient focus on real-time risk assessment	Real-time, adaptive risk frameworks
[49]	Generative AI for operational risk	30% reduction in operational inefficiencies	Lack of generalization across financial domains	Cross-domain adaptable risk models

Table 5 Framework /Platform and Model Architectures

Paper	Framework/Platform	Model Architecture
[41]	Google Cloud AI Platform	VAE (Variational Autoencoder)
[39]	AWS (Amazon Web Services)	GAN (Generative Adversarial Network)
[49]	Azure Machine Learning Studio	Transformer-based models

Table 6 AI Agent Models and Key Quantitative Findings in Stock Predictions

Paper	Model/Approach	Key Findings
[54]	Collaborative AI-agent framework	15% increase in ROI
[53]	Multi-agent stock prediction system	20% improvement in prediction accuracy

Table 7 Summary of Quantitative Findings for Financial Risk Agents

Paper	Model/Approach	Key Findings	Gaps	Future Work
[54]	Collaborative AI-agent framework	15% increase in ROI	Limited scalability for large datasets	Scalable AI frameworks for big data
[53]	Multi-agent stock prediction system	20% improvement in prediction accuracy	Lack of robustness under market volatility	Develop robust models for dynamic markets

Table 8 Models and Key Findings in Fraud Detection

Paper	Model/Approach	Key Findings
[35]	Generative AI for fraud detection	40% decrease in false positives
[48]	AI for SEC filing irregularities	92% accuracy in fraud detection

Table 9 Framework with Model Architecture Mix for GPT and LSTM

Paper	Framework/Platform	Model Architecture
[54]	Google Cloud AI	GPT (Generative Pre-trained Transformer)
[53]	Cloudera Machine Learning	LSTM (Long Short-Term Memory) networks

Table10 Framework and Model Architecture Mix for GAN and Tranformers

Paper	Framework/Platform	Model Architecture
[35]	Azure Machine Learning Studio	GAN (Generative Adversarial Network)
[48]	AWS Sagemaker	Transformer-based models

Table 11 Summary of Quantitative Findings for Financial Risk Agents

Paper	Model/Approach	Key Findings	Gaps	Future Work
[35]	Generative AI for fraud detection	40% decrease in false positives	Limited focus on new fraud patterns	Adaptive models for evolving fraud tactics
[48]	AI for SEC filing irregularities	92% accuracy in fraud detection	Over-reliance on historical data	Integrate real-time data sources

Table 12 Models and Findings in Trading

Paper	Model/Approach	Key Findings
[47]	Multimodal trading AI agent	12% increase in profit margins
[55]	Multi-agent market model	Price stabilization, reduced volatility

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Table 13 Models, Gaps, Findings and Future Work in Trading

Paper	Model/Approach	Key Findings	Gaps	Future Work
[47]	Multimodal trading AI agent	12% increase in profit margins	Limited application to small-cap markets	Extend to small-cap and emerging markets
[55]	Multi-agent market model	Price stabilization, reduced volatility	Focused on single-agent interactions	Investigate multi-agent interactions in real-time

Table 14 Model Framework Mix for Multimodal, MARL and RL

Paper	Framework/Platform	Model Architecture
[47]	Google TensorFlow Extended	Multimodal Transformer
[55]	Cloudera Data Science Workbench	Multi-agent reinforcement learning (MARL)
[23]	AWS (Amazon Web Services)	Reinforcement Learning (RL)

Table 15 Customer Support Agent Models and Findings

Paper	Model/Approach	Key Findings
[46]	Generative AI-powered support agents	35% reduction in response time
[45]	Executive strategies for AI agents	50% increase in customer satisfaction

Table 16 Gaps, Findings and Future work in Customer Support Models

Paper	Model/Approach	Key Findings	Gaps	Future Work
[46]	Generative AI-powered support agents	35% reduction in response time	Limited personalization in customer interactions	Personalized support using customer behavioral data
[45]	Executive strategies for AI agents	50% increase in customer satisfaction	Limited adoption in SMEs	Adapt strategies for small and medium enterprises

Table 17 Gaps and Future Direction

Domain	Identified Gaps	Proposed Future Directions
Financial Risk Management	Limited explainability of models (Moodys, 2023)	Using explainable AI techniques to improve transparency for Gen AI models.
	Insufficient real-time adaptability (FSB, 2024)	Using tooks like Kafka and integrating them with Devops Cloud pipelines to design adaptive and real-time risk monitoring frameworks
Investment Risk	Scalability issues for large datasets (Fatemi, 2024)	Using scalable architectures provided by cloud services. For slow-moving data, tools like Spark distributed frameworks handle large-scale financial datasets.
	Inadequate robustness in volatile markets (Han, 2024)	Using Reinforcement learning techniques developed in the field of gen AI to Develop models tailored for dynamic market conditions.
Fraud Detection	Over-reliance on historical data (Roosevelt, 2024)	Integrate real-time anomaly detection techniques and adaptive learning mechanisms may be using GAE and VANs for synthetic data
	Lack of generalization across fraud scenarios (Arize, 2024)	Diversify the input data to detect multi-domain fraud detection and making frameworks capable of learning from diverse datasets.
Stock Market Prediction	Limited application to small-cap markets (Zhang, 2024)	Extend predictive frameworks to include more granular data and merging High frequency trading data with tailored strategies.
	Single-agent focus ignoring multi-agent dynamics (Microfoundations, 2024)	Investigate the performance of multi-agent interactions in real-time trading environments for collaborative decision and data sharing strategies.
Customer Support	Limited personalization of AI responses (PwC, 2024)	Enhance personalization using user behavioral and transactional data to refine engagement using modern Emotional Integrate tailored towards AI
	Low adoption in small and medium enterprises (Cognizant, 2024)	Create cost-effective, modular AI solutions which are open source tailored for SMEs in financial services.

AI agents within financial risk management enhance credit risk assessment, regulatory compliance, and operational risk monitoring. Table 8 provides an overview of implementation frameworks and model architectures.

➢ *Investment Risk Agents*

AI agents specialized in investment risk focus on optimizing portfolio strategies and refining decision-making systems. Research by [54] proposed a cooperative AI-agent framework that boosted simulated portfolio returns by 15%. Meanwhile, [53] created a multi-agent model for stock price forecasting, achieving a 20% higher accuracy rate than traditional methods. These systems prioritize strategic portfolio enhancements and data-driven financial analysis. Critical quantitative results are detailed in Tables 7, 13, and 14, with Table 14 specifically summarizing performance metrics, identified research limitations, and future opportunities.

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Investment risk agents emphasize portfolio optimization and decision-making functions. Tables 10, 11, and 15 outline the relevant frameworks and model architectures.

- *Fraud Risk Agents*

Fraud detection and prevention represent essential fields in which AI agents demonstrate exceptional capability. [35] analyzed innovations in generative AI for identifying fraud risks, demonstrating a 40% reduction in false-positive instances within credit card fraud contexts. In a comparable study, [48] investigated generative AI applications for SEC filing analysis, identifying anomalies with 92% precision. Fraud risk agents serve to identify and mitigate fraudulent transactions within financial infrastructures.

- *Stock Market Agents*

AI agents within financial markets are engineered to forecast patterns, enhance trading operations, and improve decision processes. Research by [47] presented a multimodal artificial intelligence agent for financial trading that demonstrated a 12% profit margin improvement during actual trading simulations. Additionally, [55] introduced a market framework illustrating how AI-based traders contribute to stabilizing prices and reducing market volatility. AI agents operating in stock markets refine trading methodologies and judgment processes. Tables 13 and 14 provide numerical results, research limitations, and directions for subsequent investigation regarding how AI agents augment trading approaches and decision frameworks in stock market environments.

- *Customer Support Agents*

AI agents are revolutionizing customer support within financial services through automation of query resolution and personalization of user interactions. Research by [46] documented a 35% decrease in response time with the implementation of generative AI-powered agents. Additionally, [45] developed an executive strategy guide demonstrating methods to attain a 50% enhancement in customer satisfaction metrics.

These customer support agents enhance engagement while optimizing service operations. Tables 16 and 17 provide a synthesis of principal findings. The quantitative data indicates that customer support agents effectively improve engagement levels and optimize customer service processes.

XII. IMPLEMENTATION CHALLENGES

- *Below are key points for Workforce Transformation.*

- Gartner predicts 80% of engineers need AI upskilling by 2027 [74]
- IBM emphasizes strategic AI upskilling [75]
- KPMG survey shows skills gap concerns [76]

- *Risk Alignment in Agentic systems require careful risk management:*

- [33] examines alignment challenges
- [39] analyzes financial stability implications
- [45] provides executive playbook for adoption

- *Operational Considerations are shown below:*

- [23] outlines agent deployment strategies
- [41] tracks the rise of AI agents
- [77] notes capability expansion beyond productivity

XIII. CONCLUSION

AI agent frameworks are experiencing relatively rapid growth of which the financial industry will be the main beneficiary. The use of LLMs, multi-agent orchestration and domain-specific integrations brings a new age of automation and intelligence. When the ecosystem grows up, collaboration between academia, industry and open-source communities will play a great role in fulfilling the potential of agentic AI.This paper highlights the significant role of AI agents across diverse financial domains. The reviewed literature underscores their quantitative benefits, such as increased accuracy, reduced inefficiencies, and enhanced decision-making capabilities. Future research should further explore the ethical implications and scalability of these agents. AI agents are transforming financial practices through generative and collaborative AI technologies, improving precision, operational efficiency, and strategic decision-making. However, challenges remain, including model interpretability, scalability limitations, and adaptability constraints. Additional research is needed on hybrid architectures, real-time frameworks, and ethical deployment to address these gaps. By investigating these areas, future studies can enable smoother integration of AI agents into financial ecosystems, ensuring more effective and sustainable solutions. This paper serves as a foundation for advancing research in this evolving field. As the quantitative benefits arising from the reviewed literature are highlighted, attention made to their achievements entails greater accuracy, decreased inefficiencies, and better decision-making ability.

In this paper, a new multi-agent architecture for the advanced financial analysis has been offered. Our architecture takes advantage of the vast power of LLMs and agentic AI to allow the creation of intelligent finance agents capable of cooperating in order to solve complicated issues.

This paper outlines an extensive understanding of the topic of multi-agent-systems (MAS) in the scope of financial analysis. We argue for a paradigm shift towards "orchestrated intelligence," where MAS, empowered by Large Language Models (LLMs) and sophisticated agentic AI frameworks, can revolutionize financial decision-making. We delve into the critical aspects of agent design, communication, and coordination, drawing upon recent advancements in AI agent frameworks [20], [70], [72] and the transformative potential of agentic AI in reshaping financial services [3], [24], [78]. Our proposed architecture addresses key challenges, including data integration, explainability, and risk management, and we present a detailed evaluation strategy to assess its efficacy in complex financial scenarios.

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➢ *The survey reveals rapid advancement in AI agent frameworks and their financial applications. Key findings include:*

- Specialized frameworks (CrewAI, LangGraph) outperform general solutions for financial use cases
- Productivity gains of 50-80% are achievable in data-intensive tasks
- Risk management and trading show particularly strong benefits
- Workforce transformation remains the largest adoption barrier

Future work should address standardization and safety in financial agent systems. As [79] notes, agentic AI represents both opportunity and disruption for the financial sector.

This comprehensive survey has examined the rapidly evolving landscape of AI agent frameworks and their transformative impact on financial services. Our analysis of 30+ recent publications (2024-2025) reveals three fundamental insights:

First, modern agent frameworks like LangGraph, CrewAI, and AutoGen have matured to support mission-critical financial applications, demonstrating 50-80% efficiency gains in data-intensive tasks such as risk assessment [35] and trade execution [26]. The emergence of specialized architectures for financial markets [25] and risk management [63] underscores the domain-specific optimization required for production deployment.

Second, successful adoption requires addressing four key challenges: (1) workforce transformation through AI upskilling [74], (2) risk alignment in autonomous decision-making [33], (3) regulatory compliance in sensitive financial operations [39], and (4) integration with legacy systems [13]. Cloud-native Python libraries [19] and modular frameworks [28] are lowering these barriers.

➢ *Third, our theoretical analysis establishes formal foundations for agentic AI in finance, including:*

- Market microfoundations via agent-based modeling [25]
- Multimodal fusion for trading systems [26]
- Hierarchical risk assessment frameworks [29]

Future work should prioritize: (1) standardization of agent communication protocols, (2) development of testing benchmarks for financial agent systems, and (3) hybrid architectures combining human expertise with agent autonomy [77]. As the field progresses, the principles outlined in this survey will help financial institutions navigate the transition from experimental deployments to production-scale agentic AI solutions [45].

➢ *Challenges and Future Directions*

Future work will focus on addressing the identified challenges, including scalability, real-time performance, regulatory compliance, and integration with existing systems. The use of AI agents in areas like wealth management [80] is a promising avenue for future research.

Deploying agentic AI in finance presents challenges such as integration with legacy systems, ensuring compliance, and managing operational risks [81]. There is also a need for standardization and best practices to ensure reliability and trustworthiness.

DECLARATION

The views are of the author and do not represent any affiliated institutions. Work is done as a part of independent researcher. This is a pure research paper and all results, proposals and findings are from the cited literature.

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