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| RESEARCH ARTICLE

Multi-Agent System Orchestration: A Comprehensive Survey of Architectures and Applications

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| ABSTRACT

The orchestration of Multi-Agent Systems (MAS) has become an essential paradigm towards supporting scalable, collaborative, and intelligent problem-solving in complex settings through large language models (LLMs). In this study, a thorough survey of MAS architectures, orchestration mechanisms, communication protocols, and applications of multi-agent systems is given. It focuses on transitioning to multi-agent ecosystems coordinated by agents, which eliminate inefficiency, limited reasoning scope, and the inability to adjust. It addresses centralized, hierarchical and distributed MAS architecture, its significance, especially, orchestration in terms of task assignment, sequencing of workflow, monitoring and fault tolerance. Moreover, it discusses such important communication standards as Model Context Protocol (MCP) and Agent-to-Agent (A2A) protocols, which permit the interoperability and well-organized cooperation between agents and other agents and systems. The survey also explains regarding applications in healthcare, industry and finance, stating how MAS orchestration is transformative. Finally, it determines the key concerns, such as scalability, governance, security, and interoperability, and outlines the new trends.

| KEYWORDS

AI Agents, Orchestration, Multi-Agent Systems (MAS), Agent Communication, Large Language Models (LLMs), Model Context Protocol (MCP).

| ARTICLE INFORMATION

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1. Introduction

Artificial intelligence (AI) has become a technology that supports the multifaceted problem-solving of the majority of spheres of healthcare, finance, industry, and scientific studies [1][2][3][4]. The initial AI systems were largely specific to small and task-related activities which had low degrees of flexibility. However, due to the rapid evolution of deep learning and machine learning technologies, AI systems have now acquired the ability to perform more sophisticated reasoning, decision-making, and prediction tasks based on data [5]. Even though this has been enhanced, individual AI models are still constrained to handle large-scale, multi-step and dynamic real-world problems that may require coordination, flexibility and contextual meanings of various tasks [6].

The capabilities of AI systems have changed dramatically with the advent of large language models (LLMs) [7]. LLMs show good achievements in natural language understanding, reasoning, code generation, planning, and knowledge synthesis. Their multimodal processing capability and context-sensitive responses have widened the application of AI [8][9]. Nevertheless, despite these developments, standalone systems in which the LLMs are used have trouble with persistent memory, long-horizon planning, integration of tools, and dependable performance in complex settings. These shortcomings have prompted the need to investigate more formal and cooperative AI systems.

The concept that has been used to challenge these issues with growing popularity has been multi-agent systems (MAS). MAS is a situation where two or more intelligent agents communicate, cooperate and coordinate to attain common or personal objectives [10]. The agents can be developed with special abilities in each, which allows distributing and running tasks in parallel. This distributed design is much more efficient, scalable and robust compared to single-agent systems. The multi-agent systems also open new possibilities of complex working processes problem solving through cooperation, competition and negotiation among the agents [11].

According to this model, multi-agent system orchestration is the key to successfully coordinating and managing agents. A structured framework for distributing tasks, scheduling workflows, controlling communication, and managing errors among agents is provided by orchestration. To improve the system's dependability and performance, it ensures that the agents cooperate rather than compete. Other methods used to improve interoperability and organized communication between agents and external systems include MCP and A2A. Nevertheless, the issue of efficient orchestration framework design brings about issues of scalability, security, heterogeneity and complexity of the system. The purpose of this survey to give an in-depth review of MAS orchestration, its architectures, communication protocols, applications, and recent trends, as well as to highlight the gaps in research and future directions.

1.1 Structure of the Paper

The paper is divided into the following sections. Section 2 addresses the basics and development of MAS. Part 3 includes architectures and orchestration mechanisms. Section 4 is on communication and coordination strategies. Section 5 shows applications, challenges, and trends. Section 6 assesses literature and research gaps. Section 7 gives a conclusion to the paper and future directions.

2. Concept and Evolution of Multi-Agent Systems

Software agents utilize AI to do tasks for their consumers. They can plan, remember, decide, learn, and adjust autonomously. Generative AI and AI foundation models' multimodality fuels them [12]. AI agents can reason, learn, and judge text, voice, video, audio, and code [13]. They have the ability to learn and can help with various business procedures and transactions. Collaborating with other agents allows them to execute more intricate operations [14]. Figure 1 depicts a learning agent interacting with its environment. Percept’s from sensors are evaluated by the critic, which provides feedback to the learning element for updating the performance element. The problem generator encourages exploration, while the performance element executes actions via effectors. This feedback loop enables continuous learning and performance improvement.

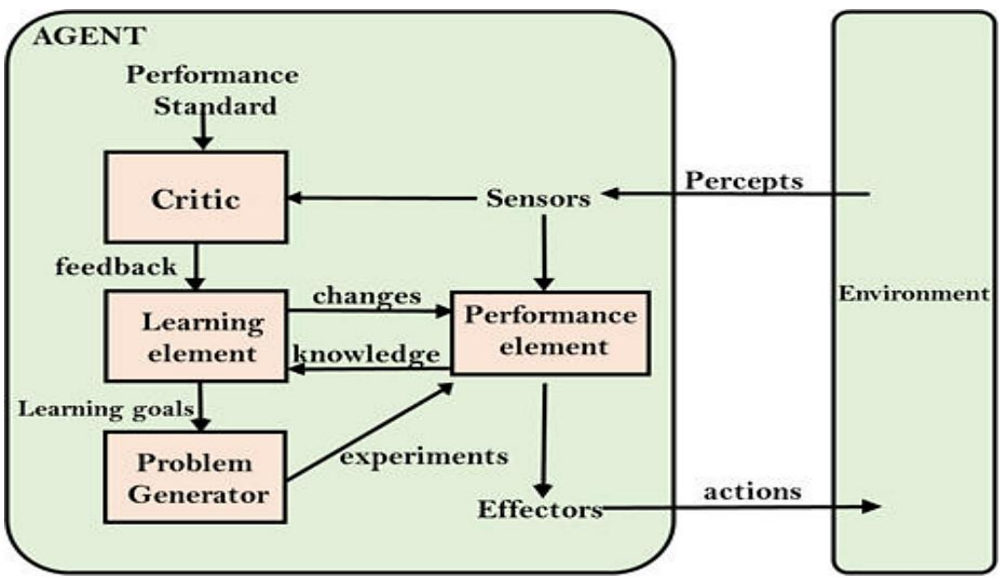

Figure 1. Structure of Agent

According to the ReAct Framework, AI agents' main features are thinking and action, although more have emerged.

- **Reasoning:** This is the basic cognitive skill which is the capacity to apply logic and the information available to one in order to formulate conclusions, inferences and resolutions. The AI agents are capable of achieving strong reasoning abilities, which allow the analysis of data, patterns, and make evidence-based and context-related decisions.
- **Acting:** For AI agents to interact with their surroundings and accomplish objectives, they must be able to act or carry out tasks in response to choices, plans, or outside information. As it pertains to embodied AI, this might comprise either digital or physical activities, such as communications, data updates, or the initiation of operations.

- **Observing:** Perception or sensing of the environment or situation is critical for AI agents to understand the context in which they find themselves and make decisions based on what they know about their surroundings. This can manifest as several forms of perception, including sensor data analysis, computer vision, and natural language processing.
- **Planning:** Intelligent behaviour involves the creation of a strategic plan to accomplish objectives. Planning AI agents are able to determine the required actions, base the possible actions on the available information and decide on the most appropriate line of action depending on the desired result. This usually entails looking into the future and taking into account possible challenges.
- **Collaborating:** Collaborating with other individuals or AI entities to accomplish a shared goal is gaining importance in increasingly complicated and ever-changing settings. Collaborating effectively requires two-way communication, teamwork, and ability to comprehend and appreciate others' views.
- **Self-refining:** One feature of develop AI systems is their capacity to self-improve and adapt [15]. Agents of self-refining artificial intelligence may acquire new knowledge, adapt their actions in response to input, and gradually enhance their capabilities and performance.

2.1 Types of Agents and System Components

The agents in MAS can be broadly categorized depending on their behavior and decision-making capabilities:

- **Reactive Agents:** A Reactive Agent is a system that reacts immediately to environmental stimuli without the need to have internal models or long-range thinking about the future. It is based on a sense-act paradigm, as the actions are based on perceptions at the moment as opposed to history or planning [16].
- **Deliberative (Cognitive) Agents:** A Deliberative Agent is a smart system that plans its actions based on an internal model of the world and reasoning procedures. It works on the sense-plan-act paradigm in that it perceives the environment, thinks over potential actions before performing the most appropriate action based on the consequences.
- **Hybrid Agents:** A Hybrid Agent is a type of Agent that integrates the capabilities of Reactive and Deliberative Agents so that it can respond quickly and plan towards goals. It involves multiple layers in which reactive behaviors deal with instantaneous cases, whereas deliberative reasoning deals with complex decision-making, and long-term planning.
- **Learning Agents:** A Learning Agent is a smart system that can enhance its performance by learning from previous experience, feedback or data. It applies a feedback loop to assess its behaviour and modify future behaviour based on it [17].

2.2 Role of Orchestration in MAS

Orchestration is the key coordination element in multi-agent AI systems that facilitates effective cooperation of the agents by controlling the flow of execution, assigning tasks dynamically, and managing the interactions. In its absence, the agents can be working in isolation, thus creating inefficiencies and failures [18]. It increases reliability through structuring work processes, monitoring progress and responding to change or mistakes in real-time. The orchestration layer as illustrated in Figure 2 aligns specialized agents, worker agents, which execute tasks, service agents, which validate and ensure quality, and support agents, which monitor and analyze. It facilitates task dependencies, provides the option to retries and allows the smooth integration of new agents, which guarantees a scalable, robust, and well-coordinated system by means of continuous feedback and adaptive decision-making.

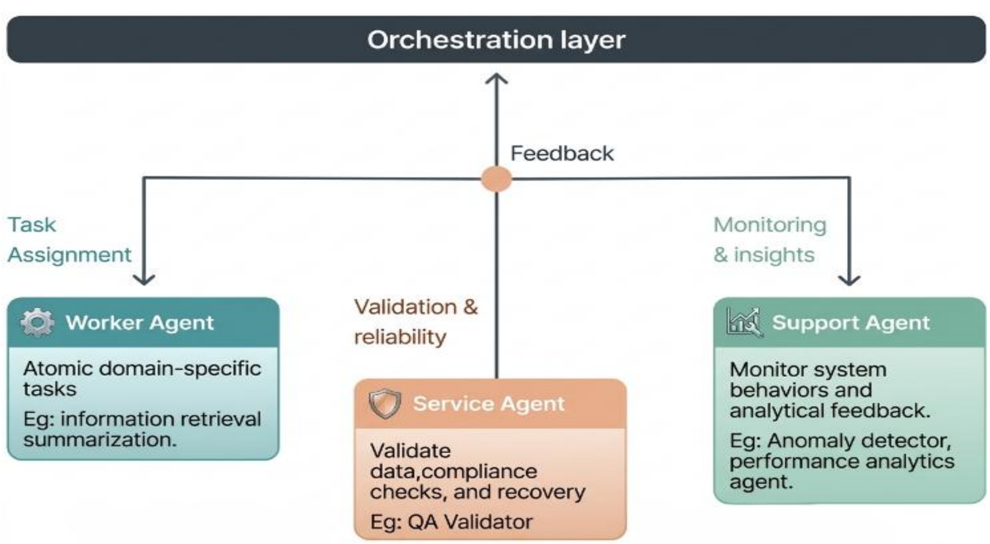

Figure 2. Orchestration Layer in a Multi-Agent AI System

Orchestration represents the core layer that maintains an order in workflows and agents in the direction of a shared purpose. The five components are the most significant:

- **Task Assignment:** Assigns each task to the agent best suited for it.
- **Workflow Sequencing:** Ensures tasks are executed in the correct order.
- **Monitoring:** Tracks progress and identifies bottlenecks.
- **Error Handling:** Retries or reroutes tasks when issues occur.
- **Communication:** Allows the agents to provide updates and context.

With these components, orchestration can be used to turn independent agents into a reliable coordinated system.

3. Architectures and Orchestration Mechanisms in MAS

In this section, centralized, hierarchical, and distributed MAS architectures are discussed and orchestration mechanisms, which facilitate task allocation, workflow execution, monitoring, and coordination between multiple agents, are explained.

3.1 Architectures of Multi-Agent Systems

It specifies the structure of a system (its structural organization) and the patterns of interaction among system agents. They define the manner in which agents interact, organize and allocate tasks in an efficient manner to accomplish common objective.

3.1.1 Centralized MAS Architecture

In centralized multi-agent system (MAS) architecture, one central coordinator manages and controls all the agents through information collection, decision making and task allocation [19]. This method gives an international perspective on the system, makes decisions easier, and enables easier implementation and management. Nevertheless, it has disadvantages of having a single point of failure, lack of scalability in large systems, and less autonomy and flexibility of individual agents in the environment. Figure 3 shows the centralized architecture.

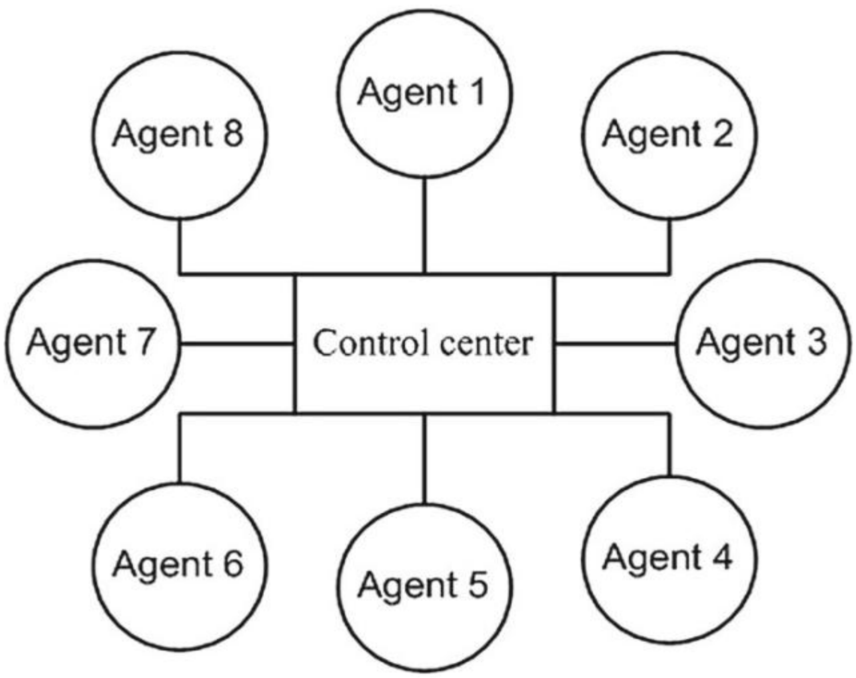

Figure 3. Centralized MAS architecture

3.1.2 Hierarchical MAS Architecture

In this approach, agents make decisions at several levels. In Figure 4, control center, agents (1–12) agents (P, Q, R, S) and agents (A, B), are listed from high to low. Agent (A, B) gathers information from Agents (P, Q, R, S) and gives control signals from control center. P, Q, R, S must gather information from Agents (1–12) and provide it to Agents (A, B) and pass control signals to them [20]. In this system, decision-making power is reserved for higher-level agents, whereas lower-level agents can only interact with those agents.

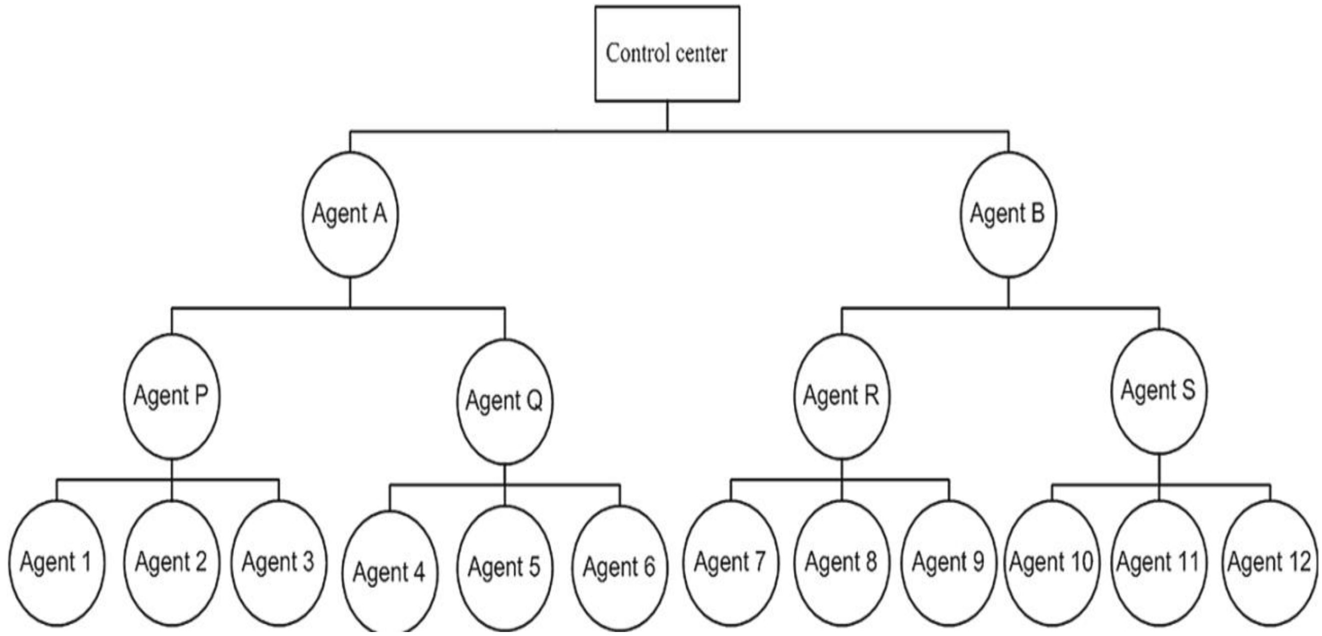

Figure 4. Hierarchical MAS architecture

3.1.3 Distributed MAS Architecture

The distributed architecture adopts a decentralized approach in which decision-making is shared among multiple agents rather than controlled by a single entity. Each Virtual Asset performs local data analysis, identifies similarities with other assets, and contributes to generating maintenance recommendations. Agents may communicate directly with one another to exchange relevant information and improve overall system performance [21]. Unlike the centralized model, clustering and recommendations are derived collaboratively through interactions among agents. This improves scalability and resilience because the system is not dependent on the point of failure. Figure 5 depicts the distributed architecture whereby interrelated agents are independent but they exchange information. It is noteworthy that the system is decentralized and collaborative, as there is no central point of control.

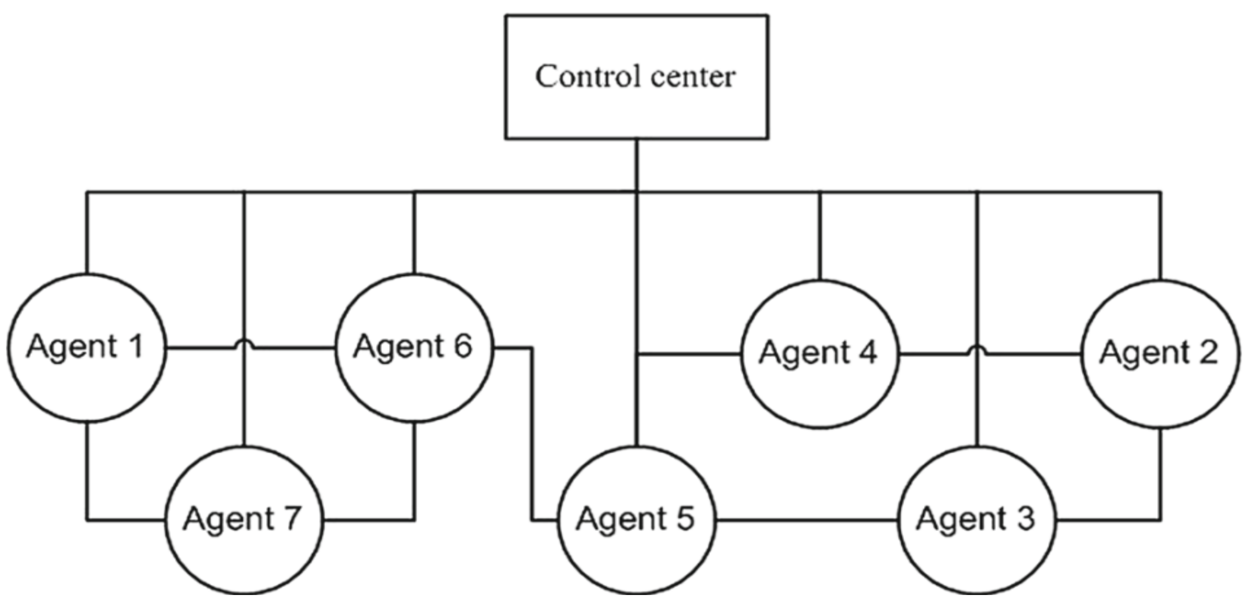

Figure 5. Distributed MAS Architecture

3.2 Orchestration Mechanisms in MAS

The mechanisms of orchestration in multi-agent systems (MAS) are those mechanisms that exist to coordinate, manage and control interactions between agents in order to accomplish system-wide goals effectively. These mechanisms characterize the manner in which tasks are allocated, workflow is organized, and communication is managed among agents. The orchestration layer, as shown in Figure 6, incorporates planning and policies, state and knowledge management, resources, quality and operations, observability tools, and runtime [22]. It is also depicted that there are several agents (worker, service, and helper) that communicate with each other via agent-to-agent (A2A) communication and Model Context Protocol (MCP), as well as using shared memory, external APIs, and toolkits. Also, such governance features as guard rails, audit traceability provide the reliability of the system, transparency, and controlled execution.

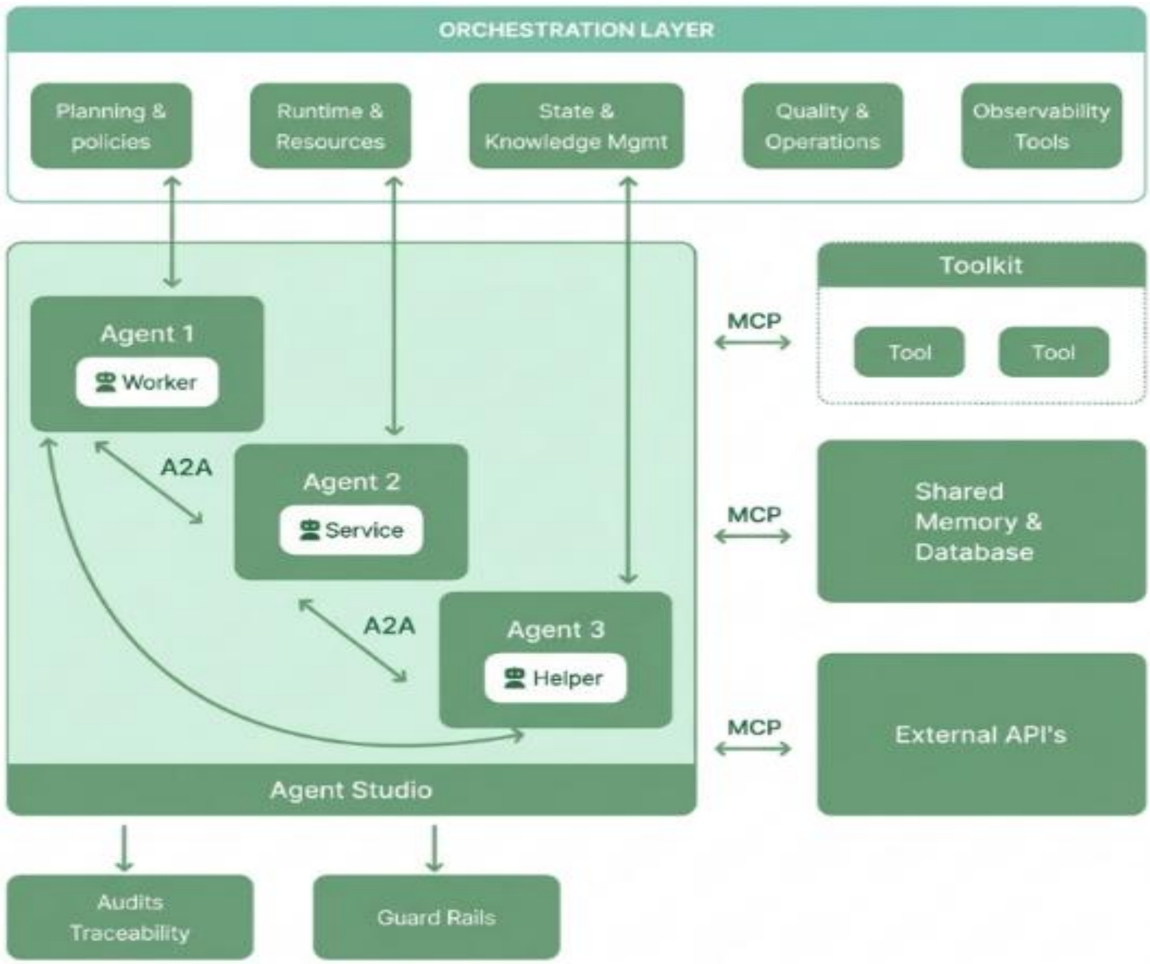

Figure 6. Orchestrated MAS Architecture

Figure 6 indicates that a centralized orchestration layer is used to ensure efficient communication and execution of tasks by coordinating various agents and resources. It also shows how tools, shared memory and external systems can be integrated to allow scalable, transparent and well-managed multi-agent operation.

4. Communication Protocols and Coordination Strategies

It includes the agent communication standards and coordination strategies, such as ACLs, MCP, and A2A protocols, which allow the exchange of information in a structured manner, interoperability, and effective cooperation between multiple agents.

4.1 Agent Communication Languages and Standards

The Agent Communication Languages (ACLs) offer a formal and structured way through which information can be exchanged in Multi- Agent Systems (MAS). They determine syntax, semantics and pragmatics of messages so that agents can communicate well in heterogeneous environments. ACLs include communication intents, called performatives (e.g. request, inform, propose), which define the intent of each interaction. ACLs facilitate semantic interoperability between agents by providing consistency of message interpretation. They may also be used in conjunction with ontologies to form a common sense of domain knowledge [23], which enhances coordination, lowers the ambiguity, and makes distributed systems more scalable. There are a number of standards that have been widely adopted, which make it possible to implement ACLs as discussed below.

- **KQML (Knowledge Query and Manipulation Language):** An initial ACL intended to share knowledge and provide query-based communication.

- **FIPA Interaction Protocols:** Predefined communication patterns like request-response and contract net techniques.
- **FIPA-ACL (developed by the Foundation for Intelligent Physical Agents):** Specifies standardized message structures, performatives and interaction protocols.
- **XML/JSON-based Messaging:** Widely used for lightweight, platform-independent data exchange in modern MAS implementations.
- **OWL (Web Ontology Language):** This is used to facilitate semantic interoperability by providing common ontologies to be used in communicating between agents.

4.2 Model Context Protocol (MCP)

The standardized interface of the interaction that operationalizes the flow of orchestration of the agents and external systems mentioned above is the Model Context Protocol (MCP). As illustrated in Figure 7, a specific interface offers schema consistency, access control, and auditability for all MCP external invocations [24]. This enables the execution unit to send tasks out with confidence so that every agent's external interaction is in line with orchestration policies and operational rules.

In MCP's client-server design, agents or orchestrators are clients that ask for external capabilities like tools, resources, or prompts. Connected systems make these capabilities available as standardized callable services.

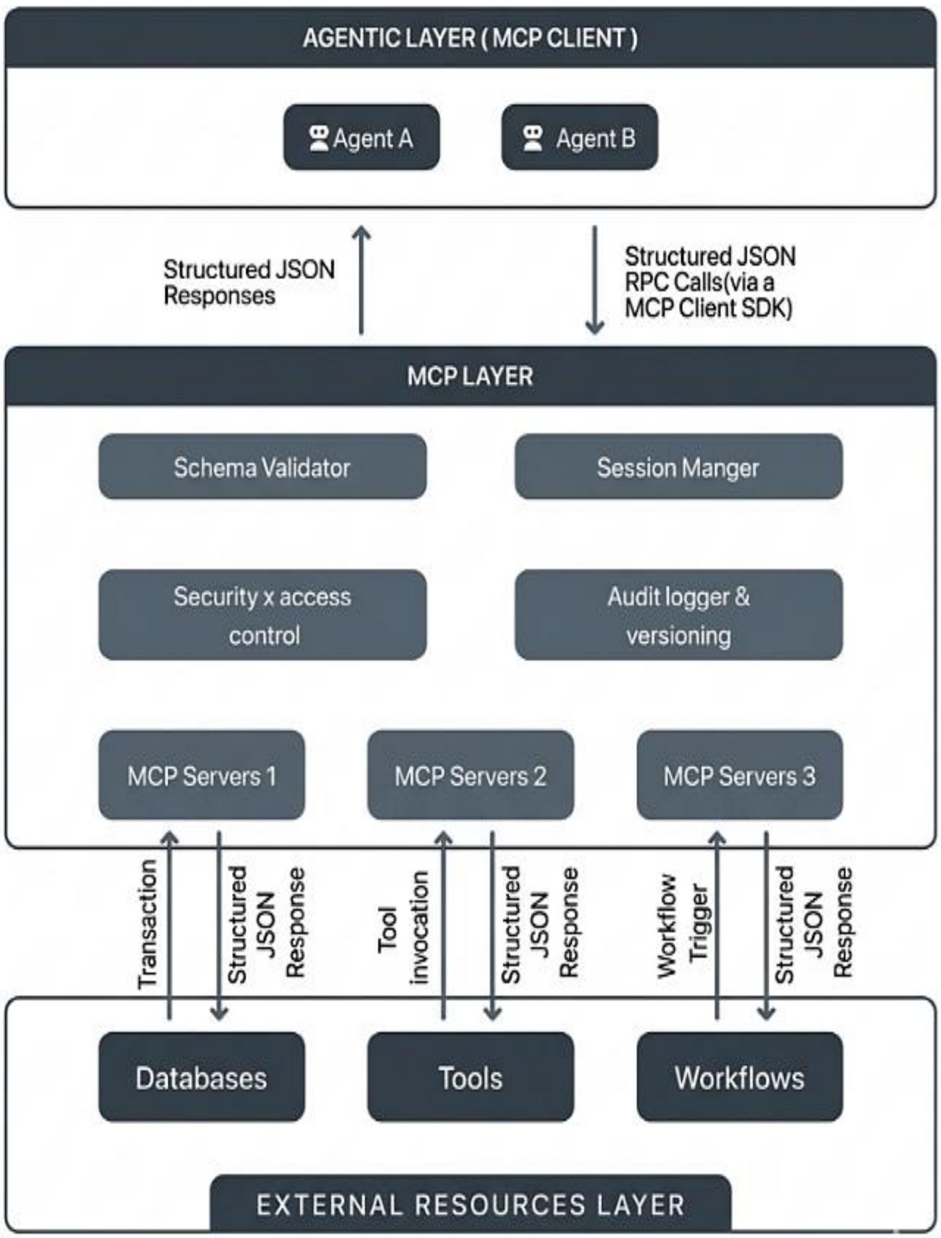

Figure 7. MCP within Orchestrated Multi-Agent Systems

4.3 Agent-to-Agent (A2A) Communication

This protocol specifies uniform communication between specialized agents, whereas MCP controls how agents interact with tools and data. It enables secure, interoperable, and delegable negotiation, delegation, and coordination across decentralized ecosystems. Agent communication is built upon two pillars: MCP, which allows agents to access tools, and A2A, which allows agents to collaborate with one another (Figure 8). A2A allows service agents to transmit diagnostic data or recovery status, worker agents to assign subtasks or discuss intermediate outcomes, and support agents to broadcast telemetry or performance insights to lead collective progress.

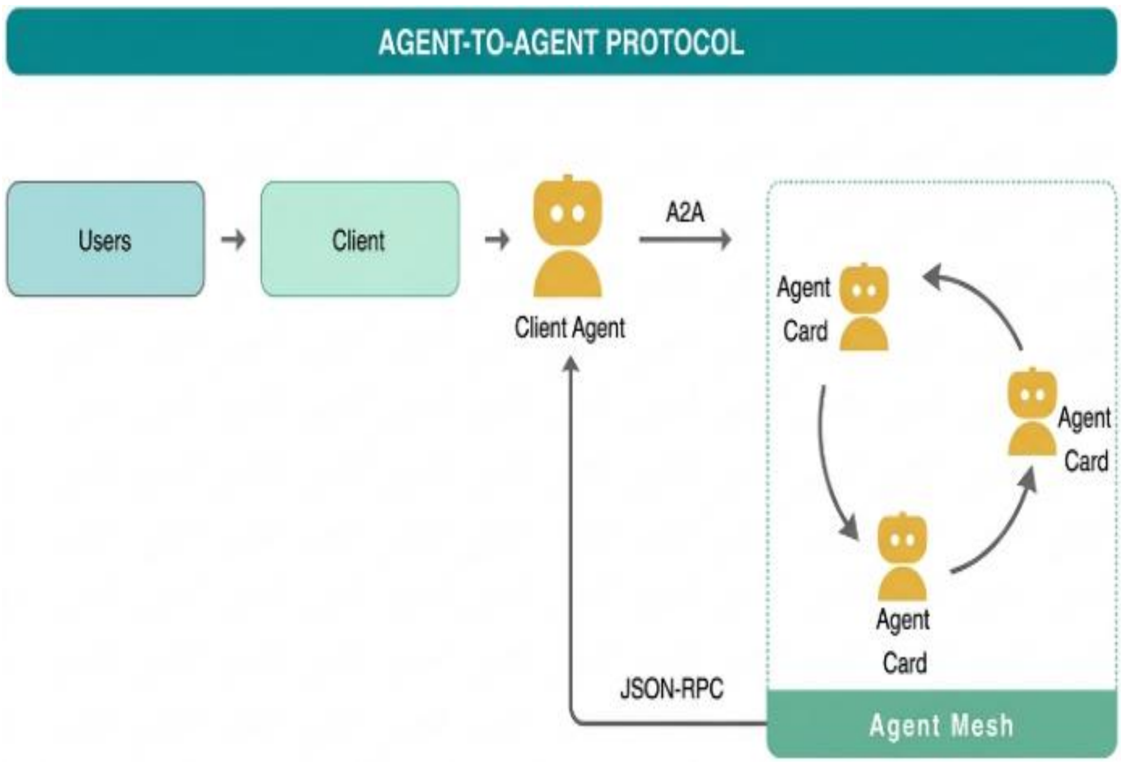

Figure 8. Agent-to-Agent Protocol

5. Applications, Challenges, and Future Directions

5.1 Real-world Applications

This section focuses on how multi-agent AI system orchestration is used in real-world fields like healthcare, industry, and finance to address complicated, multi-step issues [25].

- **Healthcare Applications:** Artificial intelligence Multi-agent coordination in healthcare allows smart coordination among the agents in charge of patient data gathering, diagnosis, treatment planning and reporting [26][27]. It is based on the systematic sequence of work in which agents are involved in analysis of medical data, identification of disease and creation of insights. This approach will improve accuracy in diagnoses, real-time tracking of patients, and compliance with the healthcare standards through validating and governing the systems.
- **Industrial Applications:** Multi-agent orchestration can be used to facilitate smart manufacturing in industrial settings, whereby agents direct manufacturing processes, control machinery, and optimize the use of resources. It allows predictive maintenance, effective scheduling and responsiveness to changes in the system. This results in reduced downtime, increased productivity, and improved operational efficiency in dynamic Industry 4.0 settings.
- **Financial Applications:** Financial sector Multi-agent orchestration may be applied to the financial industry to synchronize the decision-making of agents that handle data analysis, risk evaluation, fraud detection, and transactions. It encourages live market intelligence, is more secure with anomaly detection, and achieves regulatory compliance [28]. This results in better financial forecasting, effective operations and better customer service with automation
- **Cross-Domain Impact:** Multi-agent orchestration provides a modular and scalable framework that can be applied to various domains to deal with complex workflows. One of the most crucial components of cutting-edge AI-driven systems, it improves system dependability, allows for real-time decision-making, and makes it easier to add new agents without affecting existing operations.

5.2 Challenges and Emerging Trends

The key challenges that are common are the need to maintain trust and reliability among agents, the need to instill governance and compliance, the need to provide interoperability among different systems and the need to control cost versus ROI. Moreover, with the increase in the size of agent networks, security, consistency of context, and human control become crucial. Effective orchestration must involve a proportional combination of automation, governance and flexibility.

Multi-agent orchestration is a new kind of Internet of Agents, in which orchestrated AI systems between organizations and industries across boundaries interact securely. As orchestration structures evolve, agents will share information independently, make joint decisions, and spread intelligence across individual businesses. This development will re-architect the ways businesses will interact, operate, and compete in the AI-driven economy.

6. Literature Review

Recent literature focuses on unified architectures, communication protocols, and taxonomies of LLM-based multi-agent systems, converging on scalability, governance, collaboration, and applications, and reports challenges in planning, safety, interoperability and human-agent integration.

A. Adimulam, R. Gupta, and S. Kumar (2026) harmonize and standardize these systems' technical architecture, resulting in a cohesive architectural framework that unites orchestration, planning, policy execution, state management, and quality operations. This article explains how observability techniques, governance systems, and orchestration logic work together to keep systems coherent, transparent, and accountable [29].

Y. Lei et al (2025) examine LLM-based agents from various perspectives and propose a new taxonomy that classifies them into four main groups: reasoning-augmented agents, which use reasoning-of-thought and tool-augmented agents, tree-structured deliberation; multi-agent systems, which allow agents to communicate and solve problems together; memory-augmented agents, which keep context intact during interactions; and finally. Although the current agents have remarkable performance on structured tasks, they still have numerous areas in which they perform poorly. These are safe deployment, long-horizon planning, and mitigation of hallucinations. The study concludes with the identification of prospective research areas, such as human-agent collaboration models, multi-modal perception, and neuro-symbolic integration. The future of this dynamic field will be facilitated by the implementation of these guidelines [30].

S. Joshi (2025) investigates how AI agents and MAS undermine corporate and industry automation and service. This article surveys corporate Agentic AI and multi-agent system use. The study discusses architecture, cooperation approaches, industrial applications, and governance. The most important are: Multi-agent systems boost process efficiency by 40-60%, particular agent relation coordination protocols are key infrastructure, and human-agent collaboration requires novel stewardship and incentive models [31].

X. Li et al (2024) provide an analysis of MAS based on LLM. Create a generic framework including five essential parts: evolution, perception, profile, mutual interaction and self-action, following the process of LLM-based multi-agent systems. Much of the prior research in the area is contained in this cohesive framework. The vast problem-solving and world-simulation applications of LLM-based MAS should also be highlighted. Lastly, elaborate on some of the modern-day challenges and give an idea of the future trend in this field [32].

D. Maldonado et al (2024) introduce the FC-MAS model Framework Components in Multi-Agent System as a theoretical framework that should help to understand and standardize the integration of components and functions required to implement and manage MAS in an engineering environment. Also, you are expected to include a well-structured process flow of distributed and centralized MAS schemes that involve a sequence of interrelated jobs that include the key processes and stages of MAS implementation. It ends with the discussion of possible future research directions, including additional research on major elements, developing the standards of domain-wide terminology, and enhancing the proposed model to render it more applicable and relevant in a wider range of situations [33].

S. Jonnakuti (2023) provides a description of MAS and their interaction with cloud computing, paying particular attention to the protocols of communicating, coordinating, and deploying the agents that enable autonomy, scalability, and fault tolerance. In order to demonstrate how cloud-based MAS may simplify intricate business processes, they go over several sample applications, such as intelligent resource allocation, cross-departmental workflow coordination, and automated incident response. They look at possible solutions to technological issues such security, consistency, latency, agent heterogeneity, and monitoring. Predicting the future, such as new trends such as hybrid edge-cloud implementations, self-improving multi-agent learning systems, and agents constructed on underlying models [34].

Table 1 describes significant works on multi-agent systems in order to assist in detecting significant research gaps in agent-based AI systems, emphasizing their designs, findings, challenges, limitations, and future opportunities.

Table 1. Comparative Analysis and Research Gaps in LLM-Based Multi-Agent Systems

Author's	Study on	Key Findings	Challenges	Limitations	Future work
A. Adimulam, R. Gupta, and S. Kumar (2026)	Orchestrated multi-agent systems and communication protocols	Proposed unified architecture with Model Context Protocol and Agent2Agent protocol	Protocol standardization and orchestration complexity	Limited empirical validation in large-scale deployments	Enhancing interoperability and enterprise-scale adoption
Y. Lei et al. (2025)	Taxonomy and evaluation of LLM-based agents	Identified four agent categories and benchmarked performance	Long-horizon planning, hallucination, safety issues	Limited performance in dynamic, unstructured tasks	Neuro-symbolic integration and multimodal capabilities
S. Joshi (2025)	Agentic AI and MAS in enterprise environments	Reported 40–60% efficiency gains and importance of governance	Ethical concerns and human-agent collaboration issues	Lack of standardized governance frameworks	Development of coordination protocols and stewardship models
X. Li et al. (2024)	Framework for LLM-based multi-agent systems	Proposed five-component structure and application domains	Agent coordination and system evolution complexity	The generalized model lacks domain-specific adaptation	Adaptive and domain-aware MAS frameworks
D. Maldonado et al. (2024)	FC-MAS conceptual framework	Introduced five-layer architecture and structured workflows	Cross-domain standardization challenges	Conceptual model with limited real-world validation	Refinement and broader applicability of framework
S. Jonnakuti (2023)	Cloud-based multi-agent systems	Highlighted scalability, fault tolerance, and enterprise use cases	Security, latency, heterogeneity, monitoring	Integration complexity in cloud environments	Hybrid edge-cloud MAS and self-improving systems

7. Conclusion and Future Work

The wider use of multi-agent systems also underlines the importance of making sure that different AI agents coordinate their movements towards the realization of shared goals. Orchestration is a key element in the arrangement of the interaction of agents, distribution of tasks, and performance of functions in a coordinated and effective way. Orchestration establishes the system in which agents do not segregate but rather combine efforts, distribute tasks, and monitor them all the time since such a system allows communicating efficiently, distributing tasks, and tracking them. A number of various architectural models and coordination strategies also help this process and increase the reliability of the system, its scalability, and its overall performance. Consequently, multi-agent systems are becoming more and more competent in solving complex and multi-step problems in various fields. With increasing size and complexity of these systems, however, a variety of practical problems are more evident. The issues of coordination of relations between a large number of agents, consistency of decision-making, and reliable and safe communication remain problematic. Another question of importance is also the problem of trade-off between system efficiency and computational cost, especially in real-time. These issues need to be overcome so that the behavior of the systems in dynamic environments may be stable and reliable. Future research in the same direction ought to be undertaken to make the design and implementation of multi-agent systems in the real world easier. These are in relation to improved coordination strategies, reduced complexity of the systems and development of more reliable and scalable solutions.

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