Unlocking the Potential of Decentralized LLM-based MAS: Privacy Preservation and Monetization in Collective Intelligence

Blue Sky Ideas Track

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ABSTRACT

Recent advances in large language models (LLMs) have enabled the development of LLM agents—autonomous systems capable of perceiving their environment, reasoning about tasks, and taking actions using external tools. While existing LLM-based Multi-Agent Systems (LaMAS) have shown promising results, they are predominantly centralized, operating within specific tasks or scenarios. These centralized designs simplify coordination but are fundamentally constrained by the limited data and knowledge available within a single entity. As LLM agents see broader deployment, the complexity of tasks increasingly requires collaboration across multiple organizations and data domains. Since organizations cannot and will not fully share their proprietary data, the next frontier of artificial intelligence lies in collective intelligence through decentralized LLM-based Multi-Agent Systems (LaMAS), where LLM agents, each accessing proprietary knowledge and tools, collaborate to solve complex tasks. This paradigm is becoming not just possible but necessary with the growing adoption of LLM agents across diverse organizations. This paper explores the transformative potential of decentralized LaMAS. In decentralized settings, two key issues arise: (1) privacy-preserving mechanisms that enable meaningful collaboration while safeguarding proprietary data and knowledge, and (2) monetization and credit attribution mechanisms that incentivize continuous improvement of agent capabilities and ensure fair value distribution among participants. Our analysis reveals that addressing these challenges can unlock a new paradigm of artificial collective intelligence that overcomes the limitations. This work contributes to decentralized AI by proposing a practical framework for mechanism design that advances both technological innovation and economic sustainability in decentralized LLM Agent networks.

KEYWORDS

LLM-based MAS; LLM; data privacy; monetization

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1 INTRODUCTION

The emergence of Large Language Models (LLMs) has fundamentally transformed artificial intelligence, progressing from basic text processors to sophisticated reasoning systems capable of autonomous decision-making and multimodal understanding [23, 30]. LLM-based agents[1] have introduced unprecedented possibilities in artificial intelligence, demonstrating remarkable abilities in context comprehension and adaptive task execution [32, 33]. While these advances are significant, the true potential of LLM-based agents lies in their application within decentralized multi-agent systems. Although such systems may require greater computational resources compared to single-agent approaches, they offer crucial advantages that justify this trade-off: inherent fault tolerance through agent redundancy, natural task decomposition without explicit workflow design, and organic specialization in complex problem-solving. When one agent fails in a decentralized system, others can seamlessly continue operations, providing robust reliability that centralized systems cannot match. Moreover, while single-agent systems demand careful orchestration of execution workflows for each task type, multi-agent systems naturally emerge with collaborative specialization patterns, allowing each agent to focus on its core competencies within the larger system architecture.

Recognizing these advantages, researchers have developed **LLM-based Multi-Agent Systems (LaMAS)**, leveraging advanced network infrastructure and LLM capabilities to enable multiple agents to collaborate on complex tasks. Several foundational frameworks have emerged to facilitate this collaboration: AutoGen [31], MetaGPT [16], and AgentVerse [4] established core architectures for multi-agent orchestration, while recent innovations like AgentScope [13] and MSI-Agent [12] have advanced system robustness and scalability. These frameworks have demonstrated remarkable success

[1]For presentation brevity, in this paper, the multi-modal LLM concept [2] is merged into the LLM concept.

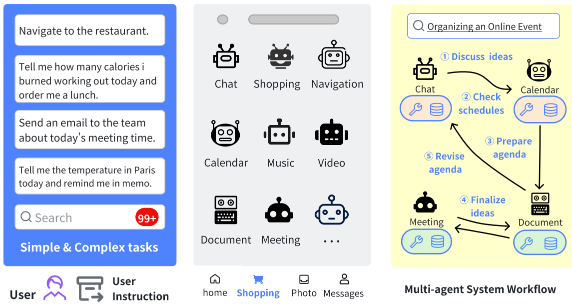

Figure 1: Illustration of LaMAS.

across diverse domains, from scientific discovery [14] and software development [24] to web interaction [5], task planning [22], and automated machine learning [28].

Despite these impressive achievements, existing approaches predominantly rely on centralized architectures, becoming increasingly misaligned with the evolving AI landscape. As major technology companies, application developers, and platform providers rapidly integrate LLM-based agents into their proprietary ecosystems, a fundamental challenge emerges: the inherent distribution of valuable knowledge and capabilities across organizational boundaries. Private enterprises, research institutions, and technology platforms are developing specialized agents that leverage their unique data assets and domain expertise, but face legitimate concerns regarding data privacy and intellectual property protection. From smart home systems to enterprise software suites, these isolated agents excel in narrow domains but lack mechanisms for cross-organizational collaboration, creating an artificial ceiling on the potential of AI.

These developments strongly suggest that the next frontier in artificial intelligence lies in enabling secure, privacy-preserving collaboration among decentralized autonomous agents. In the decentralized setting, two key issues naturally arise: (1) data-preserving mechanisms that enable meaningful collaboration while protecting organizations' proprietary data and knowledge, and (2) monetization and credit attribution mechanisms that incentivize continuous improvement of agent capabilities and ensure fair value distribution among participating entities, which become essential due to the involvement of multiple organizations.

In this paper, we present a comprehensive analysis of decentralized LaMAS by examining its technical and business landscapes. We investigate these fundamental challenges and propose a innovative mechanism design to address them. Our analysis reveals that decentralized LaMAS, supported by well-designed mechanisms, offers a practical and scalable path toward achieving collective intelligence that surpasses the inherent limitations of both centralized LaMAS and single-LLM systems. This work contributes to the emerging field of LaMAS by examining how innovative mechanism design can simultaneously drive technological advancement and ensure economic sustainability in collaborative AI ecosystems.

2 RELATED WORK AND LIMITATIONS

Coordination mechanisms define interaction strategies while architectural patterns specify their structural implementation in LaMAS. Current research has explored from centralized to decentralized approaches. However, these efforts face limitations when addressing cross-organizational collaboration challenges.

2.1 Existing Coordination Approaches

Fully Centralized Coordination: In this approach, the system maintains complete control over all engaged agents, enabling high-coordination behavior through centralized training and execution methods. While this offers optimal coordination, it requires all agents to be developed within a unified platform framework, similar to applications in an operating system, granting the data and control access to the platform. For example, when all agents are developed and deployed within a single cloud platform, they can achieve tight integration and seamless coordination. **Decentralized Coordination with Global Credit**: This system allows agents to maintain their autonomy while using credit allocation as a coordination mechanism. This is much more practical since each agent (and the entity behind it) does not have to grant the data or control access to the platform. Also, the platform can still incentivize the engaged agents to improve their collaboration performance by allocating credit to the team. For instance, in a customer service scenario, different specialized agents (e.g., for scheduling, information lookup, and problem resolution) can work together while maintaining their independence, with credits allocated based on customer satisfaction outcomes. **Fully Decentralized Coordination**: This represents the most challenging but also most flexible approach. There is no access to data or control for each engaged agent and no credit allocation for the platform, the agents in the system will need to find their own way to collaborate with others and improve themselves. The focus here shifts to mechanism design that enables emergent coordination. For example, in a cross-organizational knowledge-sharing scenario, agents must learn to collaborate while protecting proprietary information and developing trust-based relationships.

2.2 Architectural Patterns and Limitations

Figure 2 shows four fundamental practical patterns.

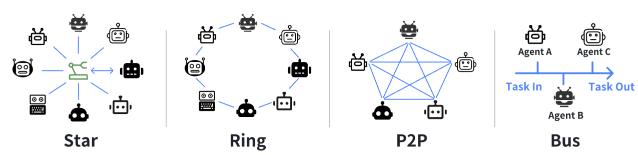

Figure 2: Architectures of LaMAS.

The **Star Architecture** [16, 24, 31] is commonly used in frameworks like ChatDev and MetaGPT. However, its central coordinator becomes a performance bottleneck and poses a privacy risk when handling sensitive cross-organizational data. The **Ring Architecture** [3, 20] is effective for sequential tasks but lacks flexibility for dynamic cross-organizational collaborations. The **Graph Architecture** [4, 34] offers greater flexibility but existing implementations lack mechanisms for privacy-preserving communication and trust establishment between organizational boundaries. Finally, the **Bus Architecture** [13, 19] faces issues due to its requirement for centralized message routing, which creates privacy vulnerabilities for cross-organizational communication. These limitations highlight the need for new coordination mechanisms specifically designed for cross-organizational LaMAS deployments. Such systems must balance efficient collaboration with privacy protection, while providing sustainable incentives for participation. We address these challenges through innovative mechanism designs that enable secure, privacy-preserving collaboration among decentralized agents.

3 PRIVACY-PRESERVING PROTOCOL

Privacy preservation is fundamental to realizing the full potential of LaMAS. As agents collaborate across organizations, they need to protect sensitive information while maintaining effective communication. Without proper privacy guarantees, organizations may be reluctant to participate in LaMAS, significantly limiting their practical applications and effectiveness. We identify 3 distinct levels of privacy concerns that require systematic analysis and novel solutions: At the **semantic level**, the challenge lies in LLMs' natural language processing, which may inadvertently reveal sensitive information through contextual associations and semantic connections. Traditional privacy mechanisms do not fully capture the complexities of semantic information leakage in natural language processing. At the **agent interaction level**, the continuous exchange of information between agents introduces privacy risks. Sensitive information can be exposed not only through direct content but also through behavioral patterns and response characteristics. Additionally, maintaining conversation history and context windows in each agent creates persistent vulnerabilities over time. At the **system architecture level**, data flows between components like model servers, caching layers, and load balancers must be secured while maintaining system performance. Additionally, the interactions of user and agents across multiple microservices and databases increase the attack surface for potential privacy breaches. Current research offers several promising directions for addressing these challenges. Homomorphic Encryption [6] enables secure computation on encrypted data, though computational complexity remains a concern. Secure Multi-Party Computation [21] provides frameworks for collaborative computation but requires optimization for LaMAS scale. Trusted Execution Environments[8] offer hardware-based security guarantees, while Differential Privacy[9] provides mathematical foundations for privacy-preserving analysis. Moving forward, research should focus on developing LaMAS-specific privacy metrics that capture semantic information leakage, creating unified privacy frameworks that integrate multiple protection mechanisms, and establishing standardized protocols for practical deployment.

4 MONETIZATION PATTERN

In this section, we outline how decentralized LaMAS will revolutionize commercialization with innovative monetization patterns. As AI capabilities of LLM Agent spread across organizations, new mechanisms for traffic and intelligence monetization will emerge.

4.1 Traffic monetization

Traffic Monetization in decentralized LaMAS represents a paradigm shift from traditional advertising systems to a decentralized, multi-organizational framework. By utilizing autonomous agents from different organizations, LaMAS will enhance advertising effectiveness while maintaining data privacy and fair revenue sharing.

Roles of Application Agents. Different types of application agents will play distinct yet interrelated roles in Traffic Monetization within decentralized LaMAS. Advertising agents will evolve beyond simply managing and deploying advertisements - they will become intelligent decision-makers that optimize ad performance across multiple organizations. Data analysis agents will transform into cross-organizational intelligence hubs that analyze user behavior patterns across multiple platforms and services. Transaction agents will advance from handling basic purchases to orchestrating seamless transactions across different platforms and services. Subscription agents will expand beyond managing individual premium services to coordinating personalized experiences across multiple organizations. These agents will enhance user retention and loyalty by understanding and optimizing the user's entire service ecosystem, supporting sustained revenue growth.

Business Scenarios and Revenue Generation. Revenue in LaMAS primarily comes from advertising, utilizing Cost Per Click (CPC) and Cost Per Action (CPA) models [18]. In the CPC model, advertisers pay based on clicks, with agents earning commissions based on their contribution to traffic management and ad effectiveness across different organizations. In the CPA model, payments are made for completed purchases, rewarding agents who drive conversions with a higher share of the revenue. Additionally, income can be generated through user subscriptions for premium features or personalized services within specific applications, such as advanced analytics dashboards or exclusive access to specialized tools. These monetization strategies are designed to operate within a decentralized framework, enabling agents from various organizations to optimize traffic flow, user engagement, and ad targeting collaboratively, thereby driving overall profitability while maintaining organizational autonomy and data privacy.

Profit Allocation Mechanisms. Converting revenue into profits that are fairly decentralized among agents from multiple organizations is key to Traffic Monetization in a decentralized LaMAS. The process starts by assessing each agent's contribution to traffic generation, ad clicks, and conversions, using metrics like CTR and CVR to quantify individual impact. To ensure fairness, LaMAS may use blockchain-based smart contracts to automate the distribution process, minimizing bias and human error. Additionally, a scoring system rates agents based on their performance, including factors like user feedback and engagement. Agents with higher scores receive a larger share of revenue, incentivizing better performance and continuous optimization. Attribution methods, such as the Shapley Value, ensure profits are allocated based on each agent's contribution to the system [26]. Dynamic adjustment mechanisms allow real-time updates to revenue shares based on agent performance and market conditions, ensuring fair compensation for optimizing traffic and ads. Incorporating metrics like CPM (Cost Per Mille) adds a more nuanced approach to revenue allocation, offering a deeper understanding of ad performance beyond just clicks and conversions [1].

4.2 Intelligence Monetization

Intelligence Monetization in LaMAS represents a significant evolution in AI commercialization by leveraging the collaborative capabilities of specialized LLM agents. Unlike traditional single-model paradigms, multi-agent systems enable dynamic interactions among specialized agents, each designed to address specific tasks, thereby facilitating the creation of more versatile and robust intelligence solutions. This paradigm has shown promise in various applications, as exemplified by recent Microsoft's Copilot Studio Platform. The platform supports an ecosystem of over 1,800 large models and offers open APIs and integration tools, enabling enterprises to incorporate agent technology into workflows and applications for enhanced customization and scalability [29].

Revenue Generation through Data-Driven Services. A key revenue model in Intelligence Monetization within LaMAS is the sale of data-driven services [11, 15, 27, 29]. Specialized agents analyze distinct datasets—such as consumer preferences, product usage, and market trends—to generate actionable insights. These insights are delivered in the form of reports, forecasts, or tailored recommendations that businesses can purchase. For instance, one agent may provide personalized user behavior insights to enhance marketing, while another offers market trend analysis to guide strategic planning. By integrating specialized agents, LaMAS offers a broad range of insights, which can be monetized through subscription models or one-time reports. In practice, successful implementations like GPT-4 API [23] have demonstrated how multiple specialized models can work in concert, with distinct agents handling different aspects of the intelligence pipeline. These include specialized agents for data processing, deep pattern recognition and insight generation, recommendation transformation, and platform integration.
Innovative Licensing and Agent Marketplaces. LaMAS also introduces novel licensing approaches that move beyond traditional software licensing. One of the most prominent is the Agent-as-a-Service (AaaS) [25], as seen in Google Cloud's AutoML, which enables dynamic agent deployment based on computational needs, with usage-based pricing and automatic scaling [7]. Complementing this will be the emergence of agent marketplace platforms, creating ecosystems for third-party agent development and deployment, as demonstrated by Hugging Face's model hub adapted for deployment of LLMs [10]. Furthermore, hybrid deployment architectures will become increasingly popular, combining on-premise agent deployment for sensitive operations with cloud-based agents for scalable tasks, as seen in IBM's Watson services which use decentralized agent architecture [17].

5 DECENTRALIZED COORDINATION DESIGN

Building on our analysis of decentralized LaMAS challenges, we propose a new architecture addressing interaction protocols, privacy, and incentives. This architecture showcases how well-designed mechanisms can effectively enable secure cross-organizational collaboration while protecting sensitive data and intellectual property. Consider two contrasting implementations that illustrate the evolution from centralized approaches to our proposed decentralized star architecture. Figure 3 depicts a conventional centralized LaMAS implementation in a music service scenario. In this design, an Orchestrator Agent serves as a central hub, coordinating interactions between specialized agents (Personal Agent, Song Agent) to process user requests. While simplifying coordination, it creates significant privacy vulnerabilities by forcing all data—including sensitive user preferences and proprietary algorithmic outputs—to flow through a single point of control. This architecture exemplifies the limitations that motivate our work: organizations must either trust a central coordinator with their sensitive data or forgo participation in the collaborative network entirely.

To address these limitations, we propose a decentralized star architecture illustrated in Figure 4 through a travel booking scenario. This design introduces three key innovations that align with our framework's core challenges: 1. **Interaction Protocol Design**: The Orchestrator Agent's role is reimagined to focus solely on high-level task decomposition and workflow coordination, operating

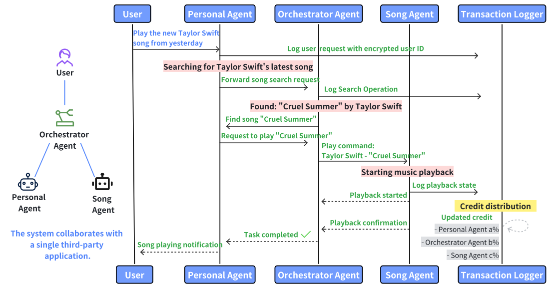

Figure 3: Centralized data handling of LaMAS.

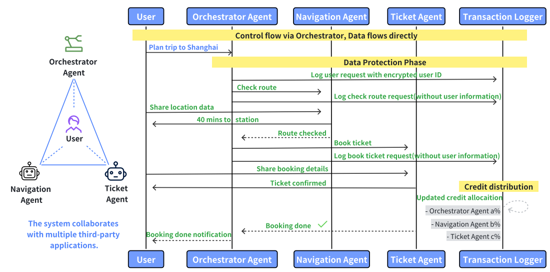

Figure 4: Decentralized data handling of LaMAS.

on abstract task descriptions rather than raw data. This clean separation between coordination and execution enables specialized agents to participate in complex workflows while maintaining their autonomy. 2. **Privacy-Preserving Collaboration**: Instead of routing sensitive data through a central coordinator, specialized agents (e.g., Navigation Agent, Ticket Agent) interact directly with user data when needed. Each agent maintains complete control over its proprietary data and algorithms, sharing only the minimum information necessary to complete assigned tasks. 3. **Incentive Mechanism Integration**: A Transaction Logger component implements our proposed credit attribution system, maintaining a record of agent contributions while preserving privacy. This enables fair compensation for participating agents based on their actual value addition, creating sustainable incentives for ongoing collaboration and capability improvement. Through this decentralized coordination design, we demonstrate how thoughtfully architected mechanisms can enable secure and effective collaboration among LLM agents across organizational boundaries. The proposed architecture addresses the key challenges of privacy preservation and incentive alignment while maintaining coordination efficiency.

6 CONCLUSION

This paper explores the potential of decentralized LaMAS, focusing on privacy and monetization challenges. We propose a novel architecture for secure cross-organizational collaboration. Our framework highlights how privacy preservation and credit attribution can incentivize participation in decentralized networks. As LLM-based agents are increasingly deployed, our mechanisms offer a foundation for secure, economically sustainable collaborative systems, overcoming the limitations of centralized approaches.

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