The 3rd Annual Summit on Decentralization & AI
The Science of Blockchain Conference 2025, U.C. Berkeley
Received: 2025-06-21 **Accepted:** 2025-07-23 **Issue Date:** 2025-08-03

Fully Decentralized Multi-agent Collaboration for the Next-generation Internet of AI agents

Jieliang Yin
Crypto-Fintech Lab, Hong Kong University of Science and Technology
jyinap@connect.ust.hk

Kani Chen
Crypto-Fintech Lab, Hong Kong University of Science and Technology
makchen@ust.hk

Youzhi Zhang
Centre fvfilltificial Intelligence and Robotics, Hong Kong Institute of Science & Innovation, Chinese Academy of Sciences
youzhi.zhang@cair-cas.org.hk

InterAgent Community
https://github.com/internetofaiagent
multiaiagentnetwork@gmail.com

***Abstract*— As LLM-based AI agents have much higher intelligence and capacity than humans, humans don't need to operate on the Internet by themselves, as their AI agents will do so for them to get and meet their demands directly. In this way, we can expect the next-generation Internet to evolve into the Internet of AI agents, and it will also become a multi-agent network that enables different AI agents to collaborate and work together. Therefore, we need to consider what the next-generation Internet of AI agents will be, and any differences from the existing Internet. What differences will AI agents and multi-agent networks make to the Internet? In this paper, we try to figure out these questions by showing that the next-generation Internet of AI agents will become more collaborative, productive, and user-friendly from the connection of individual users to collective intelligence and capacity, and also more decentralized via enhanced peer-to-peer connection and collaboration, surpassing centralized online platforms.**

Keywords*—*AI agent, Multi-agent network, Multi-agent collaboration, Internet, Decentralization, Online platforms

I. Introduction

With the rapid development of artificial intelligence, especially Large Language Models (LLMs), LLM-based AI agents are arising as they can directly get and meet the demands of users by performing all kinds of operations and finishing all kinds of tasks for users. AI agents can also communicate and collaborate with other AI agents to form a multi-agent system, which enables them to outperform a single agent in more sophisticated and challenging tasks. With more and more AI agents emerging, they fully open and connect each other to form a multi-agent network as the next-generation Internet. Based on the superior intelligence and capacity of AI agents, the next-generation Internet based on AI agents can have collective intelligence and capacity via multi-agent collaboration to better accomplish tasks for users and meet the demands of users.

However, the current Internet is highly centralized and monopolized by giant online platforms. With strong network effects, they expand and dominate the whole Internet quickly, which makes it hard to directly connect and get what they want without them. Their centralization causes many issues like vicious competition, price discrimination, one-out-of-two, and security & privacy concerns. Another issue is that the technology and business of the existing Internet are built based on real humans as users, like marketing and advertising, rather than non-human users like AI agents. Their isolation and exclusion also make the Internet fragmented, which makes AI agents hard to connect and collaborate with each other. The existing Internet limits further development of AI agents and their multi-agent collaborative network as the next-generation Internet.

As for existing multi-agent systems and networks, they are still in the early stages of development and are trying to address the fundamental issue of interoperability. For instance, Model Context Protocol (MCP) connects online servers and services to AI agents rather than connecting AI agents. Agent-to-Agent Protocol (A2A) achieves basic connection and communication among AI agents, but it's limited to the enterprise level and lacks the mechanism of multi-agent collaboration, including selection, adaptation, and coordination. The existing multi-agent collaborations are mainly centralized rather than decentralized, restricting their collective intelligence and capacity. Blockchain, crypto, and Web3 achieve a decentralized network economy via distributed ledger technology, but their inefficiency and inconvenience limit widespread usage and applications as the next-generation Internet. AI agents can make blockchain, crypto, and Web3 more capable, efficient, and convenient, and blockchain, crypto, and Web3 can facilitate the decentralization of a multi-agent network, but there is a lack of integration of AI agents and blockchain, crypto, and Web3 in decentralization.

To release the full potential of AI agents and multi-agent networks, the next-generation Internet of AI agents needs to be fully open and decentralized to be fully collaborative. It opens to all different kinds of AI agents and facilitates their collaboration to maximize the collective intelligence and capacity of AI agents. To achieve full decentralization and collaboration, the next-generation Internet of AI agents can learn from distributed technologies of blockchain, crypto, and Web3, like decentralized identity, data sharing, and zero-knowledge verification, and equip an effective mechanism for the seamless collaboration of AI agents, including agent selection, adaptation, and coordination. In this way, the next-generation Internet of AI agents can address the issues of the existing Internet and enable a better Internet to better accomplish sophisticated and challenging tasks for users and meet their demands.

Therefore, in this paper, we try to address the issues above by designing the basic structure and components of the next-generation open Internet of AI agents, and showcase how it achieves fully decentralized and unlimited multi-agent collaboration for a better Internet. Based on the current agent interoperability protocols, including MCP and A2A, we further design a highly efficient and effective collaboration mechanism of AI agents to facilitate their selection, adaptation, and coordination. We also learn from distributed technologies of blockchain, crypto, and Web3 to make the collaboration of AI agents fully decentralized. Our goal is to enable fully decentralized multi-agent collaboration for the next-generation Internet of AI agents. It would be a fully open, efficient, and collaborative multi-agent network, which can fully unleash collective intelligence and capacity of AI agents and best finish all different tasks and meet all different demands for users.

II. Literature Review

A. LLM-based AI agents

AI technology has developed for a long time, and the latest advancement is LLM, which lays a solid foundation for AI agents. LLMs primarily focus on content generation based on input prompts, while agents are designed to function autonomously within real-world environments [2]. Originally, an agent is defined as any autonomous entity that perceives its environment through inputs (e.g., user queries, sensor data) and acts upon it via outputs (e.g., API calls, messages) to achieve designated goals. Empowered by LLM, LLM-based AI agents can ingest contextual information, execute tasks, and interact with external services or tools [1]. They can have strong capacities in planning, reasoning, memory, action, and tool usage to perceive the environment and detect the demands of users, generate and execute corresponding solutions to complete certain tasks, and meet the demands of users. The main properties and core attributes of LLM-based AI agents include autonomy, sociability, reactivity, and adaptability, as they can think and act autonomously and interact with real-world environments independently [1].

B. Multi-agent system and collaboration

Besides a single AI agent, AI agents can collaborate with each other to form a multi-agent system and achieve better performance than a single agent. As different AI agents have different specialties, when they work together as a multi-agent system, they can finish more sophisticated and diverse tasks than a single agent. In a multi-agent system, several AI agents connect and communicate with each other, assign and undertake different subtasks towards a common goal together. To facilitate the collaboration of AI agents, there are different collaboration strategies, modes, and methods in multi-agent systems, including centralization or decentralization, cooperation or competition [9] [10].

There are many multi-agent system frameworks implementing and exploring multi-agent systems and collaboration. For instance, LangChain provides abstractions for chaining LLM calls, memory buffers, and function invocation in modular workflows, with built-in support for retrievers, vector stores, and agent loops. CAMEL provides a role-playing framework where a task-specific agent and two cooperating AI agents (User and Assistant) work to complete tasks via role-based conversations. AutoGen enables developers to define flexible agent behaviors and communication patterns, allowing LLM agents to cooperate through conversation and tackle complex tasks by decomposing them into manageable subtasks [9]. However, these agents are often homogeneous, and the settings of a multi-agent system are predefined. As a result, the collaboration of AI agents in the multi-agent system is also limited within the system under a particular structure and procedure.

C. Multi-agent network and interoperability

When opening and expanding a multi-agent system to incorporate heterogeneous and autonomous AI agents, we can get a multi-agent network where the collaboration of AI agents will be highly dynamic and flexible. A multi-agent network has the issue of agent interoperability, which is the prerequisite for their collaboration. Interoperability is the ability of distinct agents and systems to discover capabilities, exchange context, and coordinate actions seamlessly [1]. As different AI agents have different configurations, standards, and interfaces, it's difficult for them to connect and communicate without interconnectivity and interoperability, so they can not form a multi-agent network and work together.

To address such fragmentation and isolation among AI agents, many agent interoperability protocols have arisen. Agent protocols are standardized frameworks that define the rules, formats, and procedures for structured communication among agents and between agents and external systems. AI agent interoperability protocols standardize the interactions of AI agents so they can easily integrate and extend their capabilities by incorporating new tools, APIs, or services [2]. Existing agent interoperability protocols include Model Context Protocol (MCP), Agent-to-Agent Protocol (A2A), and Agent Communication Protocol (ACP). Model Context Protocol (MCP) is a JSON-RPC client–server interface for secure context ingestion and structured tool invocation. MCP provides a JSON-RPC client-server interface for secure tool invocation and typed data exchange. Agent-to-Agent Protocol (A2A) is a peer-to-peer framework using capability-based Agent Cards over HTTP and Server-Sent Events for enterprise-scale task orchestration. A2A enables peer-to-peer task outsourcing through capability-based Agent Cards, facilitating enterprise-scale workflows. Agent Communication Protocol (ACP) is a REST-native performative messaging layer with multi-part messages, asynchronous streaming, and observability features for local multi-agent systems. ACP introduces REST-native messaging via multi-part messages and asynchronous streaming to support multimodal agent responses [1].

However, as there are so many AI agent interoperability protocols and more and more new ones are also emerging, how to integrate or make these existing AI agent interoperability protocols becomes a new issue. If developing a new interoperability protocol to connect these protocols, like the protocol of protocols, it would incur undesirable complexity, risks, and workload, like cross-chain protocols on blockchain. If different protocols compete and finally one or a few of them unite all other protocols like previous Web1 protocols and Web2 online platforms, such standardization would stifle innovation and eliminate discrepancies unable to meet different configurations of different AI agents [3]. Moreover, for fully decentralized collaboration of AI agents in a multi-agent network, only achieving basic agent interconnectivity and interoperability is not enough.

D. Decentralization multi-agent system and Internet of AI agents

Previous research advocated decentralized multi-agent systems versus centralized ones. In a decentralized multi-agent system, each agent operates based on local information and possibly limited communication with other agents [9]. With distributed control and decision-making across agents. They form temporary coalitions to solve complex problems with collective intelligence. In this way, decentralized agent systems can have better performance and achieve better results than centralized systems [2].

Previous research also proposed the Internet of AI agents and claimed it should be decentralized. [3] advocated for a Web of Agents as an interoperable ecosystem of collaborative agents. It compared centralized and monopolistic Web of Agents with centralized and interoperable ones, and advocated decentralized Web of Agents where agents can dynamically discover each other's expertise and establish communication to tackle complex, cross-disciplinary challenges that no single agent could address alone [3]. However, none of the previous research specifically designed a feasible approach to achieve a decentralized multi-agent system as the next-generation Internet of AI agents.

III. System Design

For the next-generation fully open, decentralized, and collaborative Internet of AI agents, we design a specific structure, components, and workflow for the next-generation Internet of AI agents, and develop a corresponding demo to really implement and achieve the Internet of AI agents.

A. Dynamic Agent Card

In A2A, an agent card is a structured metadata document that includes a list of available skills, usage instructions, input/output formats, supported protocols, and authentication requirements. Agent Card acts as both an advertisement and an interface contract for interacting agents. An agent card is a good way for an agent to search and find other agents, but it does no good for agent selection and connection, which are essential for the following agent communication and collaboration.

As for agent connection, different agents have different interoperability standards and support different connection methods, and it's unrealistic, inefficient, and costly to either unify them to one standard or develop new methods to connect these different interoperability methods, as mentioned above. Without specifying supported interoperability standards and connection methods in the agent card, agents are unable to connect to any other agents with different interoperability standards and connection methods. As for agent selection, agents don't just need to know "what the agent is" or "what does the agent do" via agent description and introduction, but more importantly they need to select and match the agents that can best work with them and finish the tasks together, which requires more task-oriented and fine-grained information including the specific and real-time content, performance, and specifications. For instance, if a user asks his/her agent to buy something for him/her, when the agent finds and selects optimal shopping agents to finish this task together, it's not enough for it to only know what agents are shopping agents, but also needs to get all the purchasable items via each agent and their detailed information like description, price, and title. Only in this way can the agent know it can purchase the item user wants from which shopping agents, and work with the best shopping agent with the best item like the best price to best meet the demand of the user.

To address this issue, we design a fully dynamic and updated agent card for agents to not just search and find each other, but more importantly, connect and select the optimal agents for agent communication and collaboration. Based on the agent card in A2A, we enable AI agents to add more specific and up-to-date information for their connection methods, actual content, and doable tasks. For instance, if the agent is for streaming media, it can demonstrate the list of all the content, like songs or videos, that it can play. If the agent is for graphic design, it can show all the design tools, effects, and parameters it has. When this content is updated, their information on the agent card will also be updated to reflect the latest situation of the agent. In this way, agents can directly and easily identify the most appropriate agents that can best accomplish the task, and know how to connect them in their ways to start their communication and collaboration.

B. Adaptive Agent Connection & Communication

Traditional interoperability protocols are standardized, pre-defined, and fixed. Once determined, they can not be changed easily to meet the different requirements and demands of different users. They also exclude any other standards. Then, interoperability issues arise when different standards and protocols coexist, and additional workload is needed to develop new adaptation solutions for them. Their users also need to spare efforts to learn how to use them, which impedes their adoption. In conclusion, static and inflexible interoperability protocols cause fragmentation, incompatibility, and inefficiency, weakening rather than strengthening interoperability.

To address this issue, the agent connection and communication protocol are fully self-adaptive. Empowered by LLM, it can learn the interoperability protocols and connection methods of other agents written in their dynamic agent card mentioned above. Following their instructions, our protocol can adjust our connection methods to adapt and connect to other agents by itself. In this way, other agents can have their interoperability protocols and connection methods based on their various demands, and they just need to write down the instructions clearly on their agent card. Therefore, we change our interoperability protocol from building passive standardization and persuading other agents to proactively adapt to it, to proactively adjusting our protocol to adapt to the interoperability protocols and connection methods of other agents. Thus, our interoperability protocol can connect more agents for a wider range of interoperability with a larger network effect. We will not cause fragmentation but improve the efficiency and diversity of agent interoperability. We can also become the hub for different interoperability protocols to connect with each other to form a fully interoperable, interconnected, and inclusive Internet of AI agents.

C. *AI Agent Matching & Selection*

To maximize the collaboration of AI agents, the first step is to accurately identify and select the most suitable and capable AI agents to work with based on the requirements of the tasks. Based on the dynamic agent card above, our agent protocol can have sufficient information about the configuration and capacity of each agent to judge and select the best ones among all available agents online. Besides getting information from the agent card, the user's AI agent should also independently and critically judge and evaluate the capacity and performance of AI agents.

To achieve this goal, we divide all available AI agents online into two categories: planning agents and execution agents. Planning agents focus on analyzing the given task and generating executable and feasible solutions that aim to best accomplish the task. Execution agents will execute the given solutions and deal with any potential issues during the execution to return the best execution results for the given solution. We adopt different evaluation metrics and selection criteria for different AI agents. For planning agents, we will measure the feasibility and quality of the solutions to determine whether they can best meet the requirements of the task. For execution agents, we will test their ability and cost to finish certain tasks, and the efficiency and quality of their execution, to determine whether they can give the best execution results. For instance, for a travel planning and booking task, we will first evaluate which planning agent can produce the best travel plan that best meets the requirements of users in travel, like price, destination, and activities. After we select the best planning agent, we will also select the best execution agent that can settle down the travel plan to best accomplish the solution, such as booking the cheapest flight and reserving the best hotel. Then we can arrange their connections, communication, and collaboration to work together.

Existing research in LLM as a judge, including agent as a judge and LLM routing, can train and use LLM to evaluate, rank, and select the best LLM or agent in certain fields. However, their evaluation and selection are based on the responses of each LLM or agent, which is costly and unscalable with a growing number of tasks and LLMs or agents. To address this issue, our agent evaluation and selection will also analyze the LLM or agent itself, including internal structure, mechanism, and components to connect them to the quality of their outputs and figure out how the LLM or agent can produce superior or inferior outputs. Then we can reuse these insights to evaluate other LLMs and agents, which will significantly reduce the workload and costs of agent evaluation and selection.

D. *Decentralized Multi-agent Collaboration*

To maximize the collaboration of AI agents and fully unleash their intelligence and capacity without limitations, our agent interoperability protocol facilitates fully autonomous and decentralized multi-agent collaboration in the Internet of AI agents. Our agent interoperability protocol only evaluates and selects the best AI agents, including planning agents and execution agents, based on the demand of users, and then facilitates their independent communication and collaboration to seamlessly work together without central coordination to best accomplish the task of users.

The optimal solution can be produced by single or multiple planning agents, and if multiple agents can work together to produce a better solution than a single agent, we will select multiple planning agents and facilitate their communication and collaboration to produce a better solution. The optimal solution can also be executed by single or multiple execution agents, and if multiple agents can work together to achieve better execution results than a single agent, we will select multiple execution agents and facilitate their communication and collaboration to produce better execution results. We will also facilitate planning agents to communicate with execution agents to produce and deliver optimal solutions for execution.

E. *Agent Security & Privacy*

Learning from blockchain, Web3, and crypto, we can address the issues of security and privacy in multi-agent collaboration and maintain the decentralization of the Internet of AI agents. Each agent has its decentralized identity (DID) for other agents to find and identify it. Cryptocurrencies, especially stablecoins, can enable AI agents to freely transfer funds and pay for each other. Zero-knowledge proofs can help verify the execution results of AI agents to ensure their execution accomplishes the tasks and meets the requirements of users. Users can protect their personal data via decentralized storage like IPFS, and also have autonomy to authorize reliable agents to securely access it to get sufficient context sharing for solution planning and execution.

IV. System Implementation

We have already developed a demo of our system called InterAgent [6] and applied it in online shopping and payment. In our demo, users can put forward their requests in online shopping, like what they want to buy. Then our agent, as a user agent, will understand the demand of users, and specify it based on the personal information of the user as context and memory stored in the agent, like users' preferences, persona, and characteristics. Then our agent will send the specified user demand to all available planning agents online. Each planning agent can analyze the demand and propose the items users may want to buy with justifications. Our agent will judge and rank them to select the best planning agents providing the best solutions, and send them to the user for confirmation. Users will review them, and if they agree, they can approve and authorize execution agents to execute it. Otherwise, they can either adjust the solution or propose new requests, then our agent will make corresponding adjustments and provide a new solution.

After users confirm the items they want to buy, we will find, select, and call the corresponding execution agents, like payment agents and shopping agents. They will seamlessly communicate and collaborate to execute the solution. Payment agents like the Alipay agent will ask users to pay for the order, and transfer the funds from the user to the merchants in the shopping agents to create the order and purchase what users want. Shopping agents like the Amazon agent will process the order to arrange for the merchant to deliver the items to users. Finally, users get what they buy, and the order is completed.

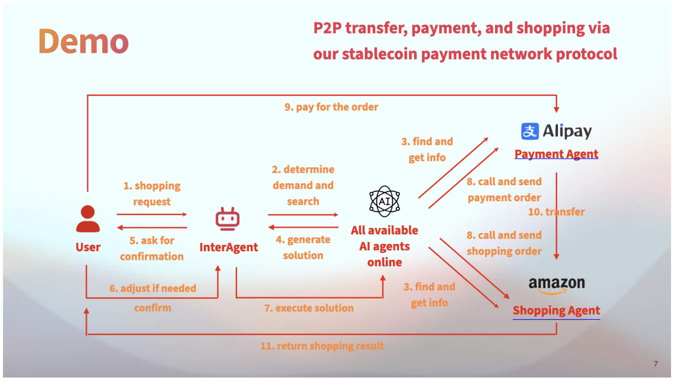

Figure I: Demo in Online Shopping

Through our demo, we demonstrate the huge benefits Internet of AI agents can bring to all kinds of applications, like online shopping. Based on the strong capacity of AI agents and decentralized collaboration in a multi-agent network, we can connect the agent of users to the agent of merchants so they can directly trade without third-party online shopping platforms, which can reduce the cost, like commission fees, for both sides. Users can easily and directly find, order, and get what they want with the best choices and prices without manual operations, which can greatly improve their efficiency and experience. Empowered by the collective intelligence and capacity of Internet of AI agents, AI agents can help both customers and merchants avoid the issues caused by the monopoly and privileges of centralized online shopping platforms, like vicious competition, price discrimination, one-out-of-two, and misleading marketing. For instance, when users shop online by themselves, they are easily manipulated by the fraudulent advertisements and marketing promotions set by the online shopping platforms and merchants to make wrong shopping decisions and buy what they actually don't want. With Internet of AI agents, users' agents can identify what users really want and help them find and buy the best items. AI agents will not be affected and misled by advertisements and promotions, and they will be fully independent and autonomous to critically and soberly evaluate each agent and item to make the best choices and get the best results for users.

V. Future Work

We are in the early stage of development, and there is still a lot of work to do. We will specify the system design above in detail, and we will also develop and implement it in practice. We will conduct systematic testing to evaluate the effectiveness and performance of our system, and verify whether it meets our goal.

References

[1] Ehtesham, A., Singh, A., Gupta, G. K., & Kumar, S. (2025). A survey of agent interoperability protocols: Model context protocol (MCP), agent communication protocol (ACP), agent-to-agent protocol (a2a), and agent network protocol (ANP). arXiv preprint arXiv:2505.02279.

[2] Yang, Y., Chai, H., Song, Y., Qi, S., Wen, M., Li, N., ... & Zhang, W. (2025). A survey of ai agent protocols. arXiv preprint arXiv:2504.16736.

[3] Sharma, R., de Vos, M., Chari, P., Raskar, R., & Kermarrec, A. M. (2025). Collaborative Agentic AI Needs Interoperability Across Ecosystems. arXiv preprint arXiv:2505.21550.

[4] Gosmar, D., Dahl, D. A., & Coin, E. (2024). Conversational AI multi-agent interoperability, universal open APIs for agentic natural language multimodal communications. arXiv preprint arXiv:2407.19438.

[5] Gosmar, D., Dahl, D. A., & Coin, E. (2024). Conversational AI multi-agent interoperability, universal open APIs for agentic natural language multimodal communications. arXiv preprint arXiv:2407.19438.

[6] Community of InterAgent (2024). Repository of Internet-of-AI-agents https://github.com/internetofaiagent/Internet-of-AI-agents

[7] Chin, D., Wang, Y., & Xia, G. (2024). Human-centered llm-agent user interface: A position paper. arXiv preprint arXiv:2405.13050.

[8] Wang, J., Xu, H., Jia, H., Zhang, X., Yan, M., Shen, W., ... & Sang, J. (2024). Mobile-agent-v2: Mobile device operation assistant with effective navigation via multi-agent collaboration. arXiv preprint arXiv:2406.01014.

[9] Tran, K. T., Dao, D., Nguyen, M. D., Pham, Q. V., O'Sullivan, B., & Nguyen, H. D. Multi-agent collaboration mechanisms: A survey of LLMs, 2025. URL https://arxiv. org/abs/2501.06322.

[10] Talebirad, Y., & Nadiri, A. (2023). Multi-agent collaboration: Harnessing the power of intelligent llm agents, 2023. URL https://arxiv. org/abs/2306.03314.