Research on the Construction of Multi-Agent Systems for Strategic Intelligence Based on Large Language Models*

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Abstract

[Objective] As the global intelligence landscape becomes increasingly complex, traditional intelligence analysis methods and simple large model demand alignment mechanisms have exhibited significant bottlenecks in addressing refined strategic intelligence tasks, necessitating urgent exploration of intelligent agent collaboration mechanisms that integrate large language models to bridge the capability gap in strategic intelligence analysis. [Method] Guided by human cognitive mapping theory, this study systematically reviews the intelligent agent design concepts from institutions such as Google, Anthropic, and Stanford, combines the practical experience of the New Generation Information Technology Strategic Research Center (CaSIT), constructs a multi-agent collaborative analysis framework, and conducts case validation through real business scenarios. [Results] The multi-agent system achieves an intelligent closed loop from intelligence requirements to decision support through deep collaboration across requirement parsing, task planning, memory storage, tool invocation, and intelligence analysis, thereby enhancing the strategic assessment capabilities of large models. [Limitations] There are limitations in understanding complex agent requirements and the deployment costs of large language models; cross-domain adaptability, unstructured data processing, and deep analysis capabilities still need to be strengthened. [Conclusion] This study constructs a strategic intelligence multi-agent analysis framework that integrates multi-source monitoring and situational awareness functions.

Full Text

Research on Multi-Agent Construction for Strategic Intelligence Based on Large Language Models

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[**Objective**] With the increasing complexity of the global intelligence landscape, traditional intelligence analysis methods and simple large model demand-alignment mechanisms have shown obvious bottlenecks in coping with refined strategic intelligence tasks. There is an urgent need to explore synergistic mechanisms of agents integrating large language models to bridge the capability gap in strategic intelligence analysis.

[**Methods**] Guided by human cognitive mapping theory, this study systematically reviews the agent design concepts of leading institutions such as Google, Anthropic, and Stanford, and combines the practical experience of the Center for Strategic Research on New Generation Information Technology (CaSIT) to construct a multi-agent collaborative analysis framework, which is validated through case studies in real business scenarios.

[**Results**] The multi-agent system achieves an intelligent closed-loop from intelligence requirements to decision support through deep synergy across requirement parsing, task planning, memory storage, tool invocation, and intelligence analysis, thereby enhancing the strategic research and judgment capabilities of large models.

[**Limitations**] The system has limitations in understanding complex requirements and the deployment costs of large language models. Its cross-domain adaptability, unstructured data processing, and deep analysis capabilities still need strengthening.

[**Conclusions**] This study constructs a strategic intelligence multi-agent analysis framework that integrates multi-source monitoring and situational awareness functions.

Keywords: Large language model, Strategic Intelligence, Intelligent Agents, Intelligent Intelligence, Intelligence Analysis
Classification Number: G202

Driven by the accelerated iteration of global technological innovation paradigms and the deepening development of interdisciplinary integration, strategic intelligence analysis is facing an information ecosystem of exponentially increasing complexity. Traditional strategic intelligence analysis relies heavily on expert judgment and manual analytical methods, which have demonstrated systematic response delays and insufficient dynamic adaptability when addressing the deep mining needs of massive, multi-source, heterogeneous data resources. Particularly against the backdrop of increasingly fierce global technological competition, decision-makers have raised new demands for the timeliness, systematicity, and foresight of intelligence analysis. These demands exhibit a generational gap from traditional analysis models in terms of data parsing capabilities, knowledge discovery pathways, and situational awareness mechanisms, constituting the core contradiction in the current paradigm shift of strategic intelligence.

The technological breakthroughs in generative artificial intelligence provide new momentum for paradigm innovation in strategic intelligence analysis. Large language models, exemplified by ChatGPT, leverage their powerful capabilities in knowledge acquisition, semantic understanding, and logical reasoning to rapidly process massive textual information and achieve real-time fusion of multi-source data and knowledge discovery. Meanwhile, AI Agent technology has demonstrated unique advantages in environmental perception, task planning, and collaborative decision-making. Therefore, combining large language models with agent technology to construct multi-agent collaborative analysis systems holds promise for overcoming the dilemmas of traditional strategic intelligence analysis and driving the realization of intelligent transformation.

Based on this, this study focuses on the application of large language model multi-agent technology in strategic intelligence analysis, aiming to construct a scalable strategic intelligence multi-agent analysis framework. By designing synergistic mechanisms among agents and establishing a human-machine collaborative analysis model, we explore a new paradigm of strategic intelligence analysis that integrates intelligent perception, analytical reasoning, and knowledge accumulation, providing theoretical and technical support for enhancing the scientificity and effectiveness of strategic intelligence analysis. The research is expected to promote deep coupling between intelligence studies and artificial intelligence technology, establishing an intelligent-enhanced methodology system with knowledge reproduction capabilities.

1.1 AI Agent Research

The breakthrough development of artificial intelligence technology is driving profound transformations in AI Agent research. Since the concept of agents was formally introduced to the field of artificial intelligence, large language model-based agent systems have made significant progress in cognitive capabilities, autonomous decision-making, and environmental adaptability. The year 2023 marked an important watershed for the field, with large language model-based agents represented by AutoGPT emerging and demonstrating powerful autonomous decision-making and task execution capabilities, triggering an industry revolution [1]. Notably, the generative agent experiment jointly conducted by Stanford University and Google validated the adaptive evolution capabilities of generative agents in complex social interaction scenarios through the "Westworld" sandbox environment [2]. As institutions such as OpenAI continue to advance agent technology research, AI agents have evolved from single task execution tools into complex systems with multiple capabilities including memory, planning, tool usage, and action [3]. Currently, research on large language model-based agents has become the mainstream direction in both academia and industry, with major institutions actively exploring how to build more efficient and reliable agent systems.

1.2 Intelligent Strategic Intelligence Research

The paradigm breakthroughs in large language model technology are reconstructing the cognitive framework and technical pathways of intelligent strategic intelligence analysis. Research from the UK' s Alan Turing Institute indicates that AI technology in strategic warning can effectively address many pain points in traditional intelligence analysis, such as time-consuming and labor-intensive processes and limited scope of manual analysis. This not only improves intelligence analysis efficiency but also creates time window advantages for decision-makers [4]. The Center for Strategic and International Studies (CSIS) further points out that we have entered a critical period for fully utilizing generative AI and large language models for strategic intelligence analysis, and have conducted a series of practical explorations in complex strategic intelligence fields such as military situation assessment and diplomatic game modeling [5][6]. Domestic academia has also begun to focus on the revolutionary role of AI technology in strategic intelligence analysis, believing it can effectively enhance the accuracy and timeliness of intelligence analysis and has unique advantages in predictive intelligence acquisition. However, current research remains primarily limited to theoretical construction, with practical applications mostly focusing on traditional machine learning algorithms. Existing research on the application of large language models in strategic intelligence analysis mostly remains at the level of simple prompt engineering and knowledge retrieval enhancement, with cognitive capabilities for complex strategic intelligence analysis tasks not yet meeting strategic decision support requirements.

1.3 Intelligence Agent Research

The continuous improvement of large language model capabilities is driving intelligence agent research to achieve dual-track advancement in theoretical construction and engineering practice. In theoretical research, scholars have systematically demonstrated the potential of intelligence agents integrating large model technology in empowering intelligence research through inductive and deductive reasoning [7], and have completed technical deconstruction studies of intelligence agents [8]. Meanwhile, some researchers have deeply explored the application of AI Agent technology in knowledge mining of scientific literature, providing important insights for practical innovation in the intelligence field [9]. In practical applications, intelligence agents have been explored in multiple domains, including emergency management [10], situational awareness [11], disinformation governance [12], patent analysis [13], and research value assessment [14]. These studies not only propose systematic concepts and specific implementation schemes for agents but also break through the limitations of single prompt engineering and knowledge retrieval enhancement, demonstrating good effectiveness in solving various complex problems. Given that strategic intelligence analysis is characterized by high complexity, high dimensionality, and composite processes, there is an urgent need to conduct more in-depth applied research on intelligence agents in this field.

2.1 The Connotation and Significance of Multi-Agent Construction

Research and application of large language models have become important drivers of strategic intelligence innovation. As shown in Table 1 , current optimization of large language models mainly includes two levels: at the fundamental technical level, model performance is enhanced through decoder optimization, network architecture improvements, and innovations in self-attention mechanisms; at the application research level, methods such as prompt engineering optimization, retrieval-augmented generation (RAG), and corpus integration are employed to improve alignment between models and intelligence requirements, enhancing model understanding and response capabilities for intelligence tasks. However, as strategic intelligence analysis scenarios become increasingly complex, this single-technology-path optimization strategy has difficulty meeting high-demand, high-precision analysis requirements. This challenge has driven the formation of the multi-agent construction concept, whose core lies in simulating human team collaboration patterns to build an intelligent intelligence analysis system with stronger adaptability and analytical capabilities.

The connotation of multi-agent construction is mainly reflected in the systematic simulation of human collaborative cognitive processes. As intelligent systems with environmental perception, task planning, and autonomous execution capabilities, agents need to not only integrate the fundamental capabilities of large models but also incorporate core technical modules such as prompt engineering optimization and knowledge graph enhancement, enabling complex task decomposition and processing through dynamic collaboration among agents [15]. This new research paradigm breaks through the limitations of traditional single models by constructing multiple agents with differentiated expertise and designing efficient synergistic mechanisms to achieve analytical depth and decision-making capabilities beyond those of single agents. Therefore, the core of multi-agent systems lies in simulating the multidisciplinary collaboration patterns of human intelligence analysis teams, providing a more scalable and adaptable technical path for strategic intelligence analysis through role division, knowledge sharing, and dynamic negotiation mechanisms.

2.2 Intelligence Agent Construction Methods

This study systematically reviews and analyzes the agent design achievements of top global institutions with extensive large model research experience, including Google, Anthropic, Stanford, and OpenAI, as shown in Table 2 . With their profound accumulation in model training, algorithm optimization, and large-scale business deployment, these institutions have not only driven the rapid development of agent technology but also possess forward-looking theoretical frameworks and practical experience in characterizing the essential features of agents and methodology construction. Therefore, based on this foundation, this study proposes an inside-out theoretical framework for agent construction. This framework forms a complete system of four progressive dimensions from the agent' s core to its external manifestation: cognitive simulation, capability construction, engineering practice, and system integration, providing important theoretical guidance and methodological support for the construction of strategic intelligence multi-agent systems, as shown in Figure 1 [Figure 1: see original paper].

Table 2 summarizes the agent design concepts of mainstream institutions:

Institution	Representative Work	Core Concept
Stanford, Microsoft Research, UC Berkeley, etc.	*Agent AI: Surveying the Horizons of Multimodal Interaction*	Agents are interactive systems that can perceive visual stimuli, language input, and other environment-based data to produce meaningful concrete real-world behaviors
OpenAI	*Practices for Governing Agentic AI Systems*	Provides definitions of AI agent systems and clarifies responsibilities and roles of parties in the system lifecycle
Anthropic	*Building Effective Agents*	When building large model agents, seek simple and general solutions

Institution	Representative Work	Core Concept
MIT	*SCIAgents: Automating Scientific Discovery Through Multi-Agent Intelligent Graph Reasoning*	Developed SciAgents that combine multi-agent reasoning systems to achieve scientific breakthroughs beyond human capabilities
Tsinghua University, Zhipu AI	*ChatGLM Agent*	Tool usage distinguishes agents from large models; agents achieve goals by observing environments and utilizing tools
Thinking Machines Lab	*AgentScope: A Flexible yet Robust Multi-Agent Platform*	Through agent frameworks, large models can perform complex operations in the human world
Lilian Weng Team	*LLM Powered Autonomous Agents*	Agent design requires versatility, convenience, and fault tolerance mechanisms

Figure 1 [Figure 1: see original paper] shows the hierarchical framework diagram of agent construction. Empirical research in cognitive science indicates that the core architecture of agent systems must be rooted in cognitive simulation mechanisms. Analysis of human complex problem-solving paradigms reveals that the synergy between prior knowledge systems and external tool chains constitutes the underlying logic of cognitive evolution. This provides key insights for agent design: in addition to possessing fundamental knowledge acquisition capabilities, agents should be able to flexibly invoke various tools to enhance their problem-solving abilities [1]. This simulation should not remain at the superficial level of copying human decision-making patterns but must delve into the essential characteristics of reasoning mechanisms and thinking processes, enabling agents to possess human-like cognitive capabilities. Google research further demonstrates that only by accurately grasping the internal laws of human cognitive processes can we construct truly intelligent systems with deep thinking capabilities [16].

On the basis of the cognitive core, functional module construction forms the basic capabilities of agents. Based on in-depth analysis of OpenAI' s agent practice cases and combined with Lilian Weng' s systematic summary of agent research paradigms, the core capabilities of agents can be summarized into four key modules: memory, planning, tool usage, and action [17][18]. Through organic integration, these modules form a complete capability chain of perception, thinking, decision-making, and action. The memory module is responsible for knowledge storage and retrieval, the planning module ensures scientific task decomposition, the tool invocation module enables flexible resource utilization, and the action module is responsible for transforming decisions into specific operations. This modular design is not only an external manifestation of cognitive simulation but also enables agents to achieve autonomous task planning and dynamically invoke required resources during execution.

Engineering practice constitutes the "growth" process of agents. At this level, Anthropic' s research particularly emphasizes the balance between system complexity and practicality, with its design guidelines recommending the principle of "simplicity first, progressive development" —starting from basic functions and gradually increasing system complexity according to actual requirements [19]. This progressive development strategy not only ensures the reliability and usability of agents at each stage but also reserves ample space for later maintenance and continuous optimization.

As the final stage of agent capability construction, system integration achieves deep interaction and collaboration between agents and the external environment. Stanford University research shows that through the organic fusion of the Agent AI framework and large language models, agents can establish more natural and efficient interactive interfaces [20]. This fusion breaks through the limitations of traditional functional stacking and, through deep optimization of the underlying architecture, fully unleashes the potential of large language models in semantic understanding and cognitive reasoning, thereby achieving seamless connection and efficient synergy between agents, the environment, and users.

2.3 Characteristics of Strategic Intelligence Analysis and Mapping

Figure 2 [Figure 2: see original paper] shows the basic capabilities diagram of intelligence agents. Strategic intelligence analysis has significant systematic, forward-looking, and strategic characteristics. According to the national positioning of strategic intelligence requirements, its core role is to provide multi-dimensional, multi-level information support for major strategic decision-making, specifically manifested in forward-looking prediction, strategic planning, professional assessment, comprehensive integration, and precise judgment.

The Yovits Decision System Theory, as one of the most influential theoretical frameworks in the intelligence field, systematically expounds the basic principles of intelligence analysis and decision support. The theory emphasizes that the intelligence analysis process should follow systematic thinking principles, scientifically evaluate options through multi-criteria decision analysis methods, employ diverse decision-making methods to support strategic judgment, and ultimately achieve high-quality intelligence-supported decision-making. This theoretical framework has not only profoundly influenced the development of modern intelligence analysis methodology but also provided important theoretical guidance for innovation in intelligence analysis paradigms in the intelligent era.

The four core elements of the Yovits Decision System Theory form systematic mapping relationships with the basic capabilities of agents and their specific implementation paths (as shown in Figure 3 [Figure 3: see original paper]): systematic thinking corresponds to the planning capability of agents, ensuring the integrity of the analytical framework and the scientific nature of execution paths through task orchestration mechanisms; multi-criteria decision analysis corresponds to thinking capabilities, supporting multi-dimensional option evaluation and deep reasoning through multi-round Q&A discussion patterns; decision method integration corresponds to tool usage capabilities, achieving precise grasp of complex decision-making environments through flexible invocation of external analysis tools; and intelligence support for decision-making corresponds to memory and retrieval capabilities, relying on knowledge base storage to achieve systematic accumulation and efficient invocation of information. This three-dimensional mapping system not only clarifies the correspondence between theoretical and technical capabilities but also provides practical guidance for the engineering implementation of strategic intelligence multi-agents through specific implementation paths.

2.4 Strategic Intelligence Analysis Process Paradigm

Figure 3 [Figure 3: see original paper] illustrates the capability mapping diagram of strategic intelligence agents. To better support the construction of large language model-based strategic intelligence multi-agents, this study systematically reviews and summarizes the strategic intelligence research paradigm of the Center for Strategic Research on New Generation Information Technology at the National Science Library, Chinese Academy of Sciences. Through long-term practice, the Center has developed a scientific and systematic strategic intelligence analysis process paradigm. This paradigm takes "requirements-intelligence (data)-analysis-decision" as the overall framework and combines multi-source data-driven evidence-based decision-making methods to construct a complete closed-loop system from requirement identification to decision recommendations. Simultaneously, this process is closely integrated with the transformation process of the DIKW model (Data-Information-Knowledge-Intelligence), achieving step-by-step progression and feedback optimization from raw data to high-value intelligence, providing important practical references for multi-agent design.

The core of the strategic intelligence analysis process lies in the organic integration of requirement identification, data collection, information extraction, knowledge discovery, intelligence generation, and feedback optimization, as shown in Table 3 . First, requirement identification is the starting point of the process.

By interfacing with the strategic needs of the Academy' s Party Group, national science and technology management departments, and local governments, it clarifies the core issues and key areas of concern to decision-makers. The core task of this stage is to transform high-level decision-making requirements into actionable intelligence research tasks, ensuring that intelligence analysis objectives are highly aligned with decision-making needs. The accuracy of requirement identification directly determines the direction and depth of subsequent intelligence analysis and is the prerequisite for ensuring the practicality of intelligence products.

In the data collection and processing stage, the Chengdu Library has constructed a diversified data acquisition system covering multi-source data including policy documents, think tank reports, academic papers, technology patents, industry reports, and research progress information. These raw data are transformed into usable information through cleaning, organization, and structuring. For example, key themes are extracted from massive literature through text mining technology, or technology development trends are identified through patent analysis methods. The core of this stage is to transform disordered data into ordered information, laying the foundation for subsequent knowledge discovery.

In the knowledge discovery and refinement stage, the Center further extracts regular and insightful knowledge through methods such as quantitative analysis, theme identification, comparative research, and case analysis. For example, it evaluates China' s competitive position in specific fields through international comparative research, or reveals potential risks and opportunities of certain technology paths through case analysis. The outcomes of this stage represent deep processing of information, forming systematic cognition of a particular field or problem. Intelligence generation and decision recommendation constitute the final output of the process. The Center transforms knowledge into forward-looking and actionable decision recommendations by integrating analysis results and expert opinions. These recommendations are presented in the form of special reports, research reports, and dynamic monitoring briefs, directly serving high-level decision-making needs. The ultimate value of intelligence is reflected in its support for decision-making, representing the highest level of the DIKW model.

To form a closed-loop feedback mechanism, the implementation effects of decision recommendations and user feedback are reincorporated into the requirement identification stage to optimize the next round of intelligence analysis. For example, effectiveness data after the implementation of a certain policy can serve as new input, and after processing through the data, information, and knowledge layers, it can further optimize the results of the next round of intelligence analysis. This closed-loop design enables the intelligence analysis process to continuously iterate and optimize, adapting to rapidly changing decision-making environments.

Within the framework of the DIKW model, the strategic intelligence analysis process achieves step-by-step progression from data to intelligence. The data layer obtains raw data through the multi-source data acquisition system; the information layer transforms data into usable information through data cleaning and structuring; the knowledge layer extracts knowledge patterns through deep analysis methods; and the intelligence layer generates high-value decision recommendations through knowledge integration and activation. This transformation process not only demonstrates the scientific nature of intelligence analysis but also provides important references for the design of core components of multi-agents such as task decomposition, data integration, knowledge discovery, and decision support. To more intuitively demonstrate the strategic intelligence analysis process and its integration with the DIKW model, Table 1 summarizes the main analysis steps and their core content.

Based on the in-depth review of the strategic intelligence analysis process and large language model application practices, combined with agent design concepts from institutions such as Google and Anthropic, this study proposes a design approach for strategic intelligence agent systems. This approach systematically elaborates the key construction points of strategic intelligence agent systems from five dimensions: reflective cognition, tool-based support, planning-based reasoning, knowledge-based fusion, and collaborative execution.

(1) **Reflective Cognition: Intelligent Modeling of Strategic Analysis Capabilities**
Strategic intelligence agents need to construct precise mapping models of human cognitive processes. Through systematic observation of strategic analysis experts' cognitive behaviors, their thinking patterns are deconstructed into four core elements: situational awareness, logical reasoning, experience summarization, and strategic judgment. This cognitive mapping is not only reflected in the formal expression of expert knowledge structures but also emphasizes the construction of self-reflection mechanisms. Through continuous self-assessment and iterative optimization, agents can continuously improve analysis quality like strategic experts. For example, when conducting major strategic situation assessments, agents can verify the integrity of reasoning processes and the reliability of conclusions through multiple rounds of self-examination.

(2) **Tool-Based Support: Capability Expansion for Strategic Intelligence Analysis**
Based on the "Tool-Using Agent" design concept, we construct a tool chain support system for strategic intelligence analysis. This system includes professional modules such as data collection tools, analysis and mining tools, and visualization tools, enabling flexible invocation through standardized interfaces. Agents can dynamically select and combine different tools according to task requirements, significantly expanding their practical capabilities in intelligence acquisition, data processing, and situational awareness. This design maintains system simplicity while reserving space for functional expansion, enabling the system to adapt to different types of strategic intelligence analysis needs.

(3) **Planning-Based Reasoning: Systematic Design of Strategic Analysis Paths**
Adopting an iterative reasoning model of "planning-execution-evaluation" to achieve systematic design of the strategic analysis process. Agents first decompose and plan complex intelligence tasks to form clear analysis roadmaps. During execution, they dynamically adjust reasoning strategies by real-time assessment of analysis progress. This planning-based reasoning mechanism is particularly suitable for handling complex problems in strategic intelligence analysis, ensuring the integrity of the analysis process and the reliability of conclusions. For example, when assessing a major strategic situation, the system first plans a multi-dimensional analysis framework covering technology, industry, and policy, then conducts in-depth research layer by layer.

(4) **Knowledge-Based Fusion: Accumulation and Application of Strategic Intelligence**
Construct a knowledge fusion system for strategic intelligence to achieve organic integration of expert experience and machine intelligence. By establishing specialized intelligence knowledge bases and precise retrieval strategies, the system can quickly invoke historical analysis cases and domain knowledge. Simultaneously, knowledge engineering methods are introduced to transform unstructured expert experience into computable knowledge modules. This fusion mechanism not only supports the system's real-time analysis capabilities but also provides technical guarantees for continuous knowledge accumulation and updating, enabling agents to continuously strengthen their professional analysis capabilities in practice.

(5) **Collaborative Execution: Multi-Agent Collaboration for Strategic Assessment**
Design a collaborative assessment framework based on multi-agents to simulate the collaboration patterns of strategic intelligence teams. Different agents assume specialized roles such as intelligence collection, data analysis, and situation assessment, forming complete reasoning chains through structured dialogue. A consensus-based decision-making model is also established to improve judgment accuracy through cross-validation among multiple agents. This collaborative execution mechanism ensures the traceability of the analysis process while enhancing the comprehensiveness and reliability of strategic judgments.

The above five-dimensional design approach forms an organic whole. Reflective cognition ensures system adaptability, tool-based support expands practical capabilities, planning-based reasoning guarantees systematic analysis, knowledge-based fusion strengthens professional depth, and collaborative execution achieves judgment reliability. These dimensions mutually support and synergistically enhance each other, collectively constructing an intelligent strategic intelligence analysis system.

Figure 3 [Figure 3: see original paper] shows the strategic intelligence agent workflow diagram.

3 Empirical Research Based on Scientific and Technological Intelligence Practice

Based on the strategic intelligence agent design principles and approaches proposed earlier, combined with the strategic intelligence business practices of the National Science Library, Chinese Academy of Sciences, this study designs an agent-driven strategic intelligence analysis process. This process achieves full-chain intelligence from intelligence requirement analysis to decision support through collaborative work among multiple agents. Figure 5 [Figure 5: see original paper] shows the specific implementation of this process, which will be elaborated in detail below regarding its design approach and the functions and collaboration mechanisms of each agent.

3.1 Strategic Intelligence Agent Operation Process

This process takes intelligence requirements as the starting point, and through stages including task decomposition, data analysis, knowledge discovery, tool invocation, and summarization, ultimately generates decision support reports and feedback optimization results. The entire process reflects the dynamic collaboration and feedback optimization mechanisms of multi-agent systems, aiming to enhance the efficiency and accuracy of strategic intelligence analysis.

In the requirement analysis stage, Agent 1, as the requirement analysis agent, receives raw intelligence requirements and transforms complex needs into structured analysis tasks through expert role positioning and core point extraction. Subsequently, Agent 2 (task planning agent) conducts global task planning based on requirement analysis results, responsible for formulating execution routes and coordinating the division of labor among agents.

The data processing stage is completed collaboratively by multiple agents: Agent 4 (memory storage agent) is responsible for interfacing with intelligence databases and quickly retrieving relevant historical data through retrieval modules; Agent 5 (tool invocation agent) completes data analysis and knowledge discovery by invoking visualization tools, clustering algorithms, and retrieval tools.

Meanwhile, Agent 3 (thinking analysis agent) conducts in-depth analysis and reasoning on the acquired information to form preliminary analysis conclusions. In the summarization stage, Agent 6 (summarization agent) systematically integrates the preliminary analysis results to generate structured analysis reports. Agent 7 (output presentation agent) is responsible for adaptively optimizing the analysis results according to original requirements to form final intelligence outputs. Additionally, the system includes a feedback module composed of Agents a, b, and c, which continuously improves system performance through ongoing result evaluation and optimization suggestions.

In multi-agent systems, agents exchange data and task status through standardized communication protocols (such as API interfaces and message queues), and dynamically allocate tasks and coordinate execution sequences through central schedulers or distributed negotiation mechanisms. In complex tasks, multiple agents can achieve task objectives through competition (such as optimal solution search) or collaboration (such as knowledge sharing).

3.2 Strategic Intelligence Multi-Agent Deployment

Figure 5 [Figure 5: see original paper] shows the strategic intelligence agent system flowchart. Based on the above design concepts and principles, combined with existing strategic intelligence business analysis, we have built this strategic intelligence agent system. The system relies on the Science and Technology Domain Strategic Intelligence Analysis Platform (SIAS) of the National Science Library, Chinese Academy of Sciences, and achieves efficient collaboration and flexible deployment of functional modules through a modular microservices architecture.

All modules are independently deployed using Docker container technology and use inter-container API interfaces for data exchange, ensuring high system availability, cross-platform compatibility, and flexible scalability. The system supports flexible selection of large language models, including locally deployed lightweight models, server-deployed medium-scale models, and mature models accessed through API interfaces. Based on actual usage requirements, data security needs, and usage time periods, the system can intelligently select the most appropriate model for intelligence analysis, thereby ensuring a balance between processing efficiency and security.

This strategic intelligence agent system further integrates multiple intelligent functional modules, including multi-source data monitoring, intelligent intelligence situational awareness, think tank report interpretation, and automated report generation, covering the complete process from data collection to intelligence analysis to report generation. Through the organic collaboration of these modules, the system can efficiently process large volumes of data, extract valuable intelligence, and provide support for strategic decision-making. Simultaneously, the platform combines open-source networking capabilities, utilizing the open-source algorithm search2ai [21] from GitHub to enhance real-time capture and analysis capabilities for global dynamic data. This technical architecture not only enhances the intelligence level of intelligence analysis but also enables the system to adapt to continuously changing strategic intelligence needs and continuously optimize and upgrade.

3.3 System and Case Selection

This study constructed a strategic intelligence analysis system based on the Meta-Llama-3-8B model from the HuggingFace platform. Through the Science and Technology Domain Strategic Intelligence Analysis Platform (SIAS) of the National Science Library, Chinese Academy of Sciences, we integrated an intelligence database containing 1,057 monitoring information sources, along with functional modules for science and technology dynamic perception and visual analysis. On this foundation, combined with the DuckDuckGo and Google online search functions provided by the search2ai toolkit, we constructed multiple agents including requirement analysis, task planning, thinking analysis, memory storage, and tool invocation, achieving full-process intelligent support for intelligence analysis.

To verify the analytical capabilities of the multi-agent system, this study selected the typical case of "The Confrontation Situation and Future Trends of Chinese and American Large Language Models in the Context of DeepSeek." This issue has significant strategic intelligence characteristics: it first requires systematic analysis of technological innovation, industrial impact, and strategic posture; secondly, it demands real-time tracking of the latest developments; and it also involves assessing the complex landscape of China-US technology competition and predicting future trends. This multi-dimensional, cross-domain analytical task tests both the system' s information processing and knowledge integration capabilities and its strategic insight and trend judgment capabilities. This study will comprehensively evaluate system performance across stages including intelligence requirement parsing, task planning and execution, data analysis and knowledge discovery, tool invocation and optimization, and intelligence output and decision support.

Experimental results indicate that the constructed multi-agent system has acquired basic strategic intelligence analysis capabilities, capable of effectively completing core tasks such as web information retrieval, professional tool invocation, and multi-round dialogue discussions, while maintaining analytical coherence through contextual memory mechanisms.

Through multi-agent collaboration, the system successfully conducted systematic analysis of the competitive landscape between Chinese and American large language models (as shown in Figure 6 [Figure 6: see original paper]), forming three core judgments across dimensions: First, from a technical perspective, DeepSeek' s innovative MoE architecture design achieves computational efficiency breakthroughs at high parameter scales, and its low-cost, high-performance technical route has produced significant impacts on the global AI industry chain. Second, from a competitive landscape perspective, China has entered the first tier of global large models, but currently exhibits a complex situation where top-level design competition coexists with industrial cooperation, while the United States maintains its leading advantage through policy control and strategic deployment. Third, from a trend prediction perspective, China-US competition will extend from the technical level to broader areas such as standard setting and industrial ecology, potentially reshaping the global scientific and technological innovation landscape. Although there remains a certain gap in analytical depth and insight compared to professional intelligence analysts, the system has demonstrated good strategic intelligence analysis support capabilities.

4.2 Sub-task Quality Analysis

Figure 6 [Figure 6: see original paper] shows a screenshot of platform results. To deeply evaluate the actual performance of the multi-agent system in strategic intelligence analysis, this study conducted systematic analysis of the operational quality of each core component (as shown in Table 4):

(1) **Basic Task Execution Assessment**: In the basic task segments based on prompt engineering, the system demonstrated good execution performance. The requirement analysis agent could accurately identify and extract core analysis needs, the task planning agent formulated reasonable execution routes, and the summarization agent maintained logical consistency and completeness of results. This reflects that the system has acquired good foundational capabilities in structured task processing.

(2) **Tool Invocation Effectiveness Analysis**: The memory storage agent achieved ideal results in knowledge retrieval and support. Through precise retrieval and correlation analysis of existing intelligence data, it effectively enhanced the depth and credibility of analysis. Its traceable analysis mechanism provides important knowledge support for strategic intelligence analysis, demonstrating the system' s advantages in knowledge management.

(3) **Memory Storage Capability Assessment**: The memory storage agent achieved ideal results in knowledge retrieval and support. Through precise retrieval and correlation analysis of existing intelligence data, it effectively enhanced the depth and credibility of analysis. Its traceable analysis mechanism provides important knowledge support for strategic intelligence analysis, demonstrating the system' s advantages in knowledge management.

(4) **Analytical Reasoning Capability Assessment**: The intelligence analysis agent can execute multi-round dialogue discussions and complete complex analytical reasoning tasks. However, it still exhibits certain divergence when handling highly complex problems, and due to the probabilistic nature of large language model computation, the consistency of multiple analysis results needs improvement. This reflects that the system still requires further optimization in deep reasoning capabilities.

It should be noted that due to space limitations, this paper omits some technical details such as fixed input-output prompt design, structured code implementation, exception handling mechanisms, and other engineering content. Although these details are essential in actual system implementation, they do not affect the understanding of the overall analytical approach and process.

Requirement: In the context of DeepSeek' s emergence, the current situation and future trends of China-US large language model confrontation.

Table 4 Strategic Intelligence Multi-Agent Analysis Process

Stage	Agent/Method	Input	Process	Output
Requirement Analysis	Prompt Engineering: Strategic intelligence expert role, core point extraction rules, nominal expression conversion	Raw requirement	Concise normalization processing	Core analysis requirements: 1. DeepSeek technical features and impact 2. China-US LLM competition status 3. Future trend prediction

Stage	Agent/Method	Input	Process	Output
Task Planning	Prompt Engineering: Task planning expert setup, resource inventory, step decomposition, agent task allocation	Core analysis requirements	Structured planning	Task execution route: 1. DeepSeek tech retrieval (tool agent) 2. China-US AI strategic query (memory agent) 3. Classification & summarization (tool agent) 4. Trend analysis (intel agent) 5. Output generation (presentation agent)
Data Collection	Web search: Key info extraction, retrieval filtering	Task execution route	Online information retrieval	Web results: 1. MoE architecture (671B params, 37B active) 2. Low-cost high-performance training 3. Global AI industry chain impact

Stage	Agent/Method	Input	Process	Output
Memory Retrieval	Knowledge base search: Strategy formulation, retrieval execution	Core requirements + task route	Intelligence DB query	Memory results: 1. US investment restrictions 2. AI defense security memo 3. Regulatory policy changes
Analysis	Clustering: K-means, LDA, cosine similarity, intelligent interpretation	All collected data	Text mining & pattern recognition	Clustering conclusions: 1. Tech position: China in first tier but gap with US remains 2. Strategic game: Coexistence of competition and cooperation 3. Competition trend: Both building competitive moats

Stage	Agent/Method	Input	Process	Output
Synthesis	Multi-agent discussion, consensus mechanism, conclusion optimization	All data + analysis results	Collaborative reasoning	Trend predictions: 1. Competition expanding to standards, ecosystems 2. Form shifting to public opinion, geopolitics 3. Impact spreading to third countries
Summarization	Process analysis, requirement matching, conclusion integration	All inputs and results	Structured synthesis	Final report: 1. DeepSeek innovation analysis 2. China-US competition assessment 3. Future trend forecast
Output	Requirement verification: completeness check, logic consistency, structure optimization	Final analysis results	Quality assurance	Intelligence products: Policy briefs, research reports, monitoring alerts

Intelligence Analysis Results:

1. **DeepSeek' s Technical Features and Impact**: DeepSeek achieves efficient computation with only 37B active parameters out of 671B total through innovative MoE architecture. Its low-cost, high-performance characteristics drive open-source community development and challenge traditional AI development models, creating profound impacts on the global

AI industry chain.

2. **China-US Large Language Model Competition Status**: China has entered the first tier of global large models but still lags behind the US in overall performance. The current landscape shows complex coexistence of top-level design competition and academic-industrial cooperation. Both sides attempt to build competitive moats through technology monopoly and ecosystem dominance, with the US maintaining leadership through policy control and strategic deployment.

3. **Future Trend Predictions**: China-US competition will deepen across algorithms, computing power, and data security, extending to public opinion, technical standards, political games, and geopolitical patterns. Intensifying competition may affect third countries, with impacts permeating finance, technology, politics, and other broad areas, presenting a comprehensive competition scenario.

4.3 Overall Research Review

Through systematic summarization of the experimental process and results, combined with the detailed analysis process shown in Table 3 and the agent design architecture discussed earlier, it can be concluded that the multi-agent system constructed in this study has achieved a complete analysis closed-loop from requirement parsing to decision support. The system demonstrates good task decomposition capabilities, knowledge retrieval capabilities, and collaborative analysis capabilities, providing a new technical path for strategic intelligence analysis. However, it should also be noted that the system still has room for optimization in terms of operational stability and result reproducibility.

5.1 Main Research Achievements

This study systematically explores the application paradigm of large language models in the field of strategic intelligence analysis. Through systematic analysis of agent design concepts from institutions such as Google, Anthropic, and Stanford, combined with the practical experience of the National Science Library, Chinese Academy of Sciences, we constructed a strategic intelligence multi-agent analysis framework based on cognitive mapping theory. This framework innovatively deconstructs and models the cognitive processes of human strategic analysis experts into four core modules: planning, memory, tool application, and reflection, achieving precise mapping of human analytical thinking. The strategic intelligence analysis technology system developed in this research integrates key functional modules such as multi-source data monitoring and intelligent intelligence situational awareness, providing comprehensive technical support for strategic intelligence analysis. Through application validation in actual business scenarios, the system has proven to have significant practical value in fields such as science and technology situation analysis and strategic early warning, effectively improving the efficiency and quality of intelligence analysis.

5.2 Innovation Analysis

At the theoretical and methodological level, this study proposes for the first time a cognitive mapping-based multi-agent construction concept, breaking through the design limitations of traditional intelligence analysis systems. By organically combining large language models with multi-agent technology, it forms a new paradigm of strategic intelligence analysis and establishes a dynamically optimized collaborative mechanism for intelligence analysis agents. At the technical implementation level, the research adopts a modular microservices architecture, achieves dynamic invocation mechanisms for multiple large language models, and innovatively designs a multi-agent discussion framework, significantly improving the reliability of analysis results. At the application practice level, the research constructs a complete strategic intelligence analysis business process, develops a series of analytical toolsets, establishes a human-machine collaborative analysis model, and achieves closed-loop support from requirements to decision-making. These innovations not only promote the deep integration of intelligence studies and artificial intelligence but also provide new approaches for the intelligent transformation of strategic intelligence analysis.

5.3 Research Limitations

This study still has several limitations. In terms of agent capabilities, the system' s understanding ability and analysis depth still need improvement when handling highly complex or ambiguous intelligence requirements. For analysis tasks requiring deep background knowledge, the system' s performance has not yet reached ideal levels, and the efficiency loss in multi-agent collaboration processes also needs further optimization. At the technical implementation level, the high deployment cost of large language models affects the system' s promotion and application to some extent; system response speed still needs optimization in scenarios with high real-time requirements; and the imperfect knowledge base update mechanism also affects the timeliness of analysis results to some degree. Additionally, as the system validation was mainly conducted in the science and technology intelligence domain, its adaptability in other domains and its unstructured data processing capabilities still need strengthening.

5.4 Future Research Directions

Based on current research achievements and limitations, future research will focus on strengthening agent learning capabilities, improving technical support systems, and expanding application scenarios. In terms of agent capability enhancement, it is necessary to deeply explore continuous learning mechanisms and knowledge transfer technologies, optimize multi-agent collaboration mechanisms, and improve system self-adaptability and overall effectiveness. In terms of technical system improvement, efforts will be dedicated to developing lightweight model deployment solutions, optimizing real-time processing architectures, and establishing dynamic knowledge update mechanisms, thereby reducing system operation costs, improving response speed, and ensuring the timeliness of analysis results. In terms of application expansion, we will actively promote system validation in more intelligence analysis domains, enhance unstructured data processing capabilities, and deepen research on human-machine collaboration mechanisms. Simultaneously, strengthening industry-academia-research cooperation is also an important direction. Through deep collaboration with intelligence practice departments to promote practical system application, academic exchanges to promote theoretical innovation, and exploration of technology transformation paths, we ultimately aim to achieve the intelligent transformation goals of strategic intelligence analysis.

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