From Management Information Systems to Intelligent Agents: Reshaping the Work Paradigm of Scientific and Technological Intelligence

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Date: 2025-06-03T15:29:46+00:00

Abstract

[Purpose/Significance] This study explores the adaptability and evolution path of Agent technology in scientific and technological intelligence work, addressing the increasingly growing demands for intelligence and cognition in intelligence operations. [Method/Process] Based on the functional evolution, capability grading, and practical patterns of Agents, this paper systematically summarizes the implementation patterns of Agents in research and intelligence work. Combined with theoretical paradigms of intelligence studies and technology evolution trends, it focuses on analyzing the evolution path from Management Information System (MIS) to Intelligence System (IS) and then to Documentation and Information Service Agent (DIS Agent), as well as the reshaping of intelligence work patterns this triggers. [Result/Conclusion] The study finds that Agents, through capabilities such as multimodal perception, process-oriented execution, and multi-agent cluster collaboration, drive intelligence work to transition from an "information management platform" based on MIS to a "dynamic cognitive service system", heralding the advent of the DIS Agent era. Meanwhile, the role of intelligence professionals transforms from "full-process dominance" to "task intent setter" and "process quality supervisor", significantly enhancing task adaptability, execution capability, and intelligence level.

Full Text

From MIS to DIS Agent: Reshaping the Paradigm of S&T Documentation and Information Service

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Abstract

[**Purpose/Significance**] This paper explores the adaptability and evolutionary trajectory of agent technology in the field of S&T documentation and information service (DIS), responding to the growing demand for intelligence-driven and cognitive-oriented capabilities in DIS work. [**Method/Process**] Based on the functional evolution, capability hierarchy, and practical application patterns of agents, the study systematically summarizes their deployment in scientific research and intelligence work. It integrates insights from theoretical paradigms and technological evolution trends, with a particular focus on analyzing the evolutionary path from Management Information Systems (MIS) to Intelligence Systems (IS) and finally to Documentation and Information Service Agents (DIS Agents), as well as the resulting transformation of DIS work modes. [**Result/Conclusion**] The findings reveal that agents—featuring multi-modal perception, process-driven execution, and multi-agent cluster collaboration—are propelling the transformation of DIS work from traditional "information management platforms" rooted in MIS toward a "dynamic cognitive service system," heralding the advent of the DIS Agent era. Meanwhile, the role of DIS analysts has evolved from "full-process dominators" to "task intention definers" and "process quality supervisors," significantly enhancing the adaptability, execution capacity, and intelligence level of DIS work.

Keywords: DIS Agent, management information systems (MIS), human-multi-agent synergy, S&T documentation and information service (DIS), new paradigm

Classification Codes: TP18; G35

With the rapid evolution of artificial intelligence (AI) technologies such as large language models (LLMs) and multi-agent collaboration, agent technologies represented by Auto-GPT†, BabyAGI‡, and MetaGPT[1] are gradually becoming key pathways for multi-domain task adaptation and autonomous execution. Agents, with their closed-loop capabilities of "perception-cognition-execution," have achieved a leap from single-tool systems to multi-agent clustering and distributed collaboration, not only driving the automation and intelligence of research processes but also demonstrating unprecedented adaptation potential in intelligence work.

Building upon the construction of DIS Agents[2, 3], this paper systematically reviews the evolutionary trajectory of agent technology and its practical pathways and capability leaps in scientific research and intelligence domains, analyzing how agents have evolved from information management tools to integrated and collaborative "intelligent partners." On this basis, we further explore the profound transformation of intelligence work modes, summarizing their core characteristics and future development trends. Through systematic exposition of the 契合 evolutionary logic between agent technology and intelligence work, this paper aims to provide theoretical support for the transformation of intelligence work in the "DIS Agent era."

- This work is supported by Major Program of National Social Science Fund of China titled "Research on the Application of Key Technologies for Intelligent Information in the Context of Digital-Intelligent Transformation" (Grant No. 23&ZD228).

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† https://github.com/Significant-Gravitas/AutoGPT ‡ https://github.com/yoheinakajima/babyagi

1 Theoretical Foundation and Capability Evolution of Agents

Amid the rapid evolution of AI, agents are becoming a core technological means for achieving task automation and intelligence. This chapter systematically reviews the conceptual origins, functional characteristics, and capability evolution of agents, clarifying how they achieve capability leaps from single-function systems to complex task construction within the continuous feedback loop of "perception-cognition-execution," providing a theoretical foundation for subsequent analysis of intelligence service system adaptability and cross-domain generalization capabilities.

1.1 Concept and Theoretical Origins of Agents

In AI research and development, agents are typically defined as autonomous computing systems capable of perceiving environments, making decisions, and executing actions, with the core goal of achieving preset tasks or utility optimization[4]. This definition highlights the "perception-cognition-execution" closed-loop structure, demonstrating three key features that distinguish agents from general IT application systems: goal-orientation, autonomy, and environmental adaptability.

Conceptually, the notion of agents is rooted in philosophical teleology and will autonomy, while also being deeply influenced by modern AI technologies. Aristotelian teleology posits that action is a conscious process toward goals[5], Kant's concept of "autonomy of the will" elaborates on the intrinsic motivation of individual behavior[6], and Turing's "imitation game" introduced the perspective of verifying intelligence through interaction, requiring AI to achieve dynamic adjustment in environmental adaptation[7]. The 1956 Dartmouth Conference formally established the AI research agenda, laying the foundation for the disciplinary development of agents[4].

1.2 Functional Attributes and Taxonomy of Agents

To systematically describe the capability boundaries of agents, researchers have proposed multi-dimensional attribute and type models. Wooldridge and

Jennings' four-dimensional agent model—Autonomy, Reactivity, Proactiveness, and Sociality[8]—has become the theoretical foundation for characterizing agent capabilities. With the widespread application of large models, researchers have further introduced new metrics such as learnability, task generalization, and long-term memory management[9]. These metrics have been incorporated into multi-agent system performance testing, revealing that current systems still face challenges like weak generalization and difficulty in maintaining context in complex tasks[10].

In terms of classification, Lu Ruqian et al.[11] categorized agents into six types based on structural complexity and capability characteristics: Passive, Reactive, BDI (Belief-Desire-Intention), Social, Evolvable, and Persona-based. This taxonomy reveals the capability leap from low-level behavioral response to high-level human-like cognitive models. Among them, the BDI agent model demonstrates significant advantages in complex plan generation and intention modeling, serving as an important foundation for understanding multi-modal agent systems[12].

In recent years, agent research has shifted from static functional classification to task adaptation and dynamic capability composition. For instance, the AgentVerse system[13] achieves multi-agent collaborative execution through modular composition and capability migration; the OpenAGI framework[14] integrates task graph mechanisms and role assignment strategies, improving system division efficiency and task elasticity; and multi-agent behavior graph modeling methods[15] further support task scheduling and optimization of complex behaviors. These studies drive agents from structural characterization toward dynamic behavioral adaptation, enhancing their practical usability across environments and tasks.

1.3 Development Stages and Capability Levels of Agents

The evolution of agent capabilities is not simply technological stacking but rather a continuous enhancement of autonomy and adaptability within the "perception-cognition-execution" closed loop. Academia typically divides agent development into three stages: The first stage comprises rule-driven systems represented by MYCIN and DENDRAL, which rely on manual knowledge bases and are limited to closed domains[16]; the second stage includes learning-driven systems represented by AlphaGo and OpenAI Five, which leverage reinforcement learning to achieve strategy optimization in dynamic environments[17]; the third stage encompasses closed-loop execution agents like Auto-GPT, CAMEL, and ReAct, which, based on large models, can already perform task decomposition, tool chain invocation, and multi-round interaction, demonstrating higher-level adaptive and dynamic interaction capabilities[18]. This developmental path not only highlights the capability leap from human-controlled to autonomous task execution but also lays the foundation for systematic capability grading of agents.

To this end, the AI community has constructed an L1–L4 capability grading model[19, 20] (see Figure 1 [Figure 1: see original paper]) to measure the leap from tool invocation (L1) to multi-round state tracking and self-adjusting strategies (L4). Although current LLM-based systems still face bottlenecks in task persistence and generalization, tests like AgentBench[10] show that agents have already acquired prototype features such as multi-round context maintenance, reflective output, and weak closed-loop execution, 预示着 the potential for evolution toward higher-level autonomous task systems.

Figure 1 Agent Capability Levels

Overall, agents are evolving from modular tools toward clustered, task-driven "task engine" architectures. With the widespread deployment of large model platforms such as GPT-4[21], PaLM 2[22], and Claude 3§, agents have acquired capabilities in multi-modal perception, context understanding, and cross-domain adaptation, laying the foundation for new paradigms like "embodied agents" and "self-driven agents"[9]. This also provides solid technical and cognitive support for the subsequent analysis of the morphological characteristics of DIS Agents and their adaptability in intelligence work.

§ https://claude.ai/login#features

2 Technical Implementation Mechanisms of Agent Systems

Agent systems are evolving from single-module drivers toward integrated architectures that span modalities and environments. Li Feifei et al.[23] proposed the Multi-modal Agent AI framework, which clearly presents the integration path of "perception-cognition-execution-interaction" mechanisms in virtual and physical environments. Among these, "perception-cognition-execution" constitutes the core closed loop of agents, while interaction serves as the external interface, reflecting the overall leap of agent systems driven by multi-source data. The overall structure is shown in Figure 2 [Figure 2: see original paper]. Based on this, this paper analyzes from three dimensions: system architecture, key capability support, and collaborative mechanisms.

Figure 2 Agent Structure[2]

2.1 System Architecture and Interaction Mechanisms

The closed-loop capabilities of agents rely on modular architectures and dynamic interaction mechanisms. Mainstream systems generally adopt a layered structure, divided into perception, cognition, and execution control modules to support multi-modal input and stable operation under complex tasks[24]. The perception layer integrates multi-source data such as text, images, and audio through architectures like Transformers to achieve semantic modeling and environmental adaptation. Typical systems like Voyager can integrate natural language instructions and environmental states into a unified representation space, enhancing contextual interaction capabilities[25].

The cognition layer, centered on LLMs, undertakes task understanding, sub-goal generation, and reasoning chain construction. The ReAct framework demonstrates plan generation and causal reasoning based on natural language[18]. The execution layer transforms language plans into specific operations through API scheduling and tool invocation. The Plan-and-Act framework decouples before and after execution[26] and combines context buffering mechanisms, significantly improving multi-round task execution stability and tracking capabilities[27].

Overall, the "perception-cognition-execution" three-layer architecture has been engineering-validated in open-source platforms such as OpenAgents[28], AgentVerse[13], and ChatDev[29]. These platforms use large language models as the scheduling core, combined with tool interfaces and state management, to initially achieve continuous task flows from instruction understanding to operation execution and result tracking. Although still facing challenges in multi-round state management and execution stability, they have already demonstrated the prototype of agent-based task execution.

2.2 Key Capability Support Driven by LLMs

As the central engine of agents, LLMs have reshaped their behavior generation and planning paradigms. Unlike traditional systems that rely on rule templates, LLMs can directly generate goal structures and execution paths through deep semantic parsing and structured mapping of natural language. Systems like Plan-and-Act[26] and Auto-GPT[30] demonstrate that LLM-driven agents possess the ability to autonomously generate sub-task trees, invoke external tools, and complete chain execution.

LLMs have also significantly enhanced agents' feedback response and strategy adjustment capabilities. Relying on memory mechanisms and context expansion, agents can track task status and generate reflective output in multi-round tasks, initially demonstrating "language-driven behavioral learning"[9]. The integration of Chain-of-Thought reasoning and interface invocation[31] has further facilitated the formation of a "goal-strategy-execution-feedback" closed-loop model. AgentBench[10] tests also show that LLM-Agents with dynamic planning and tool scheduling capabilities significantly outperform single LLMs in complex tasks.

Furthermore, the pre-trained knowledge transfer capability of LLMs enables agents to possess cross-task generalization and zero-shot execution potential when facing unseen tasks, marking their evolution from customized tool systems to autonomous task executors.

2.3 Technical Foundation for Multi-Agent Collaborative Operation

Faced with multi-dimensional challenges from complex tasks, the limitations of single-agent systems have gradually become apparent, spurring the development of Multi-Agent Systems (MAS)[32]. MAS achieves distributed collaboration for complex tasks through role division, information sharing, and task scheduling[33]. It typically uses Task Graph mechanisms to dynamically map global tasks, supporting concurrent multi-tasking and contextual elasticity. The CAMEL system enhances generation efficiency through multi-role division in scientific writing[15], while the OpenAGI framework optimizes task dependency and context connection using graph structures[14]. Modern platforms also achieve game-like multi-round interaction through structured message passing and context sharing (such as the Multi-Agent Debate Framework)[34].

In terms of scheduling control, MAS needs to balance centralized coordination and distributed autonomy. AgentVerse introduces round-robin scheduling and dynamic weight adjustment to enhance consistency[13]; MetaPolicy achieves dynamic resource optimization based on reinforcement learning[35]; EvolveGraph improves the adaptability and interpretability of group agents through dynamic relational graph reasoning[36]. With the integration of LLMs and multi-modal technologies, MAS has been engineering-validated in scenarios such as research assistance and urban governance, demonstrating stronger collective intelligence potential.

2.4 Technical Bottlenecks and Application Adaptability Analysis

Despite significant progress in multi-modal fusion, language-driven control, and multi-agent collaboration, true "task closed-loop" has not yet been fully achieved. In complex multi-round tasks, agents exhibit deficiencies in context modeling and task tracking, manifesting as context loss, link breakage, and strategy drift, which affect execution coherence and self-healing capabilities. Meanwhile, current systems mostly rely on black-box LLM interface calls, lacking fine-grained state perception and dynamic correction mechanisms. Although multi-agent collaboration has preliminary division of labor and task scheduling, it still lacks unified context management and efficient communication protocols, easily leading to execution failure or deviation[37].

These technical bottlenecks limit the leap of agent systems from "tool integration" to true "task closed-loop." In the future, with continuous optimization of state modeling, cross-agent communication protocols, and multi-round memory mechanisms, agents are expected to achieve breakthroughs in multi-agent collaboration, context maintenance, and full-link consistency, laying the foundation for higher-level autonomous intelligent task systems.

3 Pathways and Evolution of Agent Technology in Practice

With the rapid application of agent technology in scientific research and other fields, agent systems have demonstrated an evolutionary path from shallow to deep in terms of capability levels, organizational forms, and task adaptation. Based on four typical systems shown in Table 1 , we analyze their specific characteristics and performance in research tasks, and summarize how agents evolve when tackling cross-domain complex tasks.

Table 1 Four Typical Agent Application Systems

Agent Type	Perception-Response	Planning-Execution	Multi-Agent Collaboration	Closed-Loop Exploration
Capability Level	L1–L2: Research Task Perception & Immediate Feedback	L3: Research Cooperation Goal Understanding & Execution Path Planning	L3–L4: Research Cross-Module Adaptation & Distributed Collaboration	L4: Scientist Autonomous Generation & Self-Reflection
Task Control Method	Passive Response	Human-Machine Collaboration Mode: Human Dominant, Agent Executes	Local Active Planning: Human and Agent Jointly Refine	Collaborative Strategy Dominant: Human High-Level Supervision, Agent Executes

3.1 Perception-Response Agent Systems

As the starting point of agent development, perception-response systems primarily handle basic tasks such as information retrieval, content classification, and single-round Q&A in research. Their typical characteristic is the "single-round input-immediate feedback" mode, where agents lack the ability to autonomously identify goals and rely on external instruction-driven operation. Core capability modules include input parsing, external data retrieval, and response generation. With the development of multi-modal perception and conversational retrieval models, such systems are gradually evolving toward capabilities for context maintenance and chain task execution. Table 2 summarizes representative practices of this system type.

Table 2 Typical Cases of Perception-Response Agent Systems

Agent Name	DeepResearch[38]	PaperQA[39]	LangGraph[40]
Function	Multi-step Research Information Retrieval & Report Generation	Literature Retrieval-Enhanced Research Q&A	Semantic Path Mapping & Cross-Literature Retrieval

Agent Name	DeepResearch[38]	PaperQA[39]	LangGraph[40]
Human Role	Set Retrieval Goals, Screen & Evaluate	Ask Questions, Screen & Track Results	Task Proposal & Interactive Exploration
Agent Role	Text Extraction, Key Information Synthesis	Multi-Literature Multi-step Research Report Generation	External Knowledge Base Multi-Modal Information Retrieval
System Features	Retrieval-Augmented Generation Driven Efficient Q&A	Graph-Based Semantic Modeling & Dynamic Response Generation	Cross-Literature Retrieval Path Visualization

3.2 Planning-Execution Agent Systems

Building upon perception-response capabilities, these systems integrate task planners, tool schedulers, and dynamic feedback mechanisms, possessing the ability to transform user goals into executable paths. Their typical capabilities include task decomposition, tool scheduling, and execution feedback, with representative cases shown in Table 3 . Although these systems demonstrate good adaptation to research scenarios, they still face three major bottlenecks[18, 41]: First, reliance on static LLM generation without dynamic multi-round state correction; second, short execution chains lacking cross-stage tracking and connection; third, dispersed tool scheduling with imperfect state management, prone to process breakage. Overall, they represent critical engineering prototypes for advancing toward closed-loop agents.

Table 3 Typical Cases of Planning-Execution Agent Systems

Agent Name	AutoDev[42]	ChemCrow[43]	Biomedical AI Agent System[44]
Function	Code Generation & Development	Chemical Experiment Planning & Execution	Life Science Hypothesis & Experiment Design Support

Agent Name	AutoDev[42]	ChemCrow[43]	Biomedical AI Agent System[44]
Tool Scheduling Capability	LLM-Based Natural Language Task Decomposition	Integration of Chemical Databases & Knowledge for Experiment Generation	Integration of Bioinformatics Tools & Control of Experimental Platforms
Human-Machine Collaboration Mode	Human Provides Requirements, Agent Autonomously Generates & Debugs Code	Scientist Defines Experiment Goals, Agent Plans & Executes Simulations	Scientist Sets Problems, Agent Generates Experiment Paths & Executes

3.3 Multi-Agent Collaborative Systems

With the deepening complexity of research tasks and interdisciplinary integration, Multi-Agent Systems (MAS) have gradually emerged. MAS emphasizes forming efficient collective intelligence networks through role division, dynamic communication, and heterogeneous collaboration among agents. Their core characteristics include multi-role division, information sharing, and dynamic interaction, with typical cases shown in Table 4 . MAS not only supports cross-module adaptation for complex research problems but also provides new scalable models for group-based modeling of research organizations. Currently, collaboration consistency, semantic alignment, and execution stability remain key challenges, which are expected to be addressed in the future through improved multi-agent memory mechanisms and dynamic communication protocols to further enhance collective intelligence modeling capabilities.

Table 4 Typical Cases of Multi-Agent Collaborative Systems

Application Domain	GVIM Assistant System	AGENTiGraph[46]	OpenAGI[14]
Agent Roles	Laboratory Director, Senior Chemist	Intelligent Knowledge Graph Task Classification, Summarization	General Task Scheduling, Writing, Searching

Application Domain	GVIM Assistant System	AGENTiGraph[46]	OpenAGI[14]
Collaboration Method	Task Assignment (Director-Led), Group Discussion, User Feedback Evolution	Each Agent Processes Independently Based on Prompt Engineering, Interactive Querying	Hierarchical & Distributed Expert Collaboration, Pipeline-Style, Orchestration Layer Coordination
System Features	Knowledge Graph Shared Context, Prompt Engineering Chains Information	Dynamic Task Decomposition, Agents Share Subtasks, Context-Based Collaboration	Heterogeneous Multi-Agent Network, Dynamic Subtask Allocation, Shared Context Pool, Task Graph & Prompt Flow Combination

3.4 Closed-Loop Exploration Agent Systems

Closed-loop exploration systems represent the advanced form of agent technology development, possessing the ability to actively discover new patterns from data, form research hypotheses, and self-correct. They embody the full closed-loop of "perception-thinking-hypothesis-verification-learning," marking a leap from research assistant to "exploration partner." Their core capabilities lie in autonomous task decomposition and execution, dynamic state tracking and strategy adjustment, and cross-round self-correction mechanisms. Table 5 summarizes typical cases and main characteristics of such systems. Despite remaining challenges in stability and generality, these systems 预示 the advanced evolutionary trends of agents in research knowledge discovery and cross-domain tasks.

Table 5 Typical Cases of Closed-Loop Exploration Agent Systems

Agent Name	Auto-GPT[30]	DiscoveryBench[47]	HypoGeniC[48]
Function	General Task Exploration	Scientific Hypothesis Generation	Social Science Reasoning
Data Source	Public Internet Information, User Data	Published Papers, Structured Data	News, Comments, Wikipedia
Closed-Loop Features	Task Decomposition, Tool Invocation, Short-term Memory, Self-Reflection	Inductive Reasoning Generation, Hypothesis Self-Generation & Validation	Cross-Domain Data Integration & Hypothesis Generation
Human Role	Set Initial Goals, Monitor Process, Evaluate Final Results	Provide Research Questions & Data, Evaluate Hypothesis Quality	Assess Novelty & Feasibility of Hypotheses, Design Follow-up Validation Plans

3.5 Summary of Agent Technology Practical Applications

Through systematic analysis of the performance and task adaptation methods of four types of agent systems in research scenarios, four key characteristics of agent applications have emerged. First, the integration trend of "large models-small scenarios" is increasingly evident. LLMs, as the core engine for semantic understanding and reasoning generation, combined with modular combinations of 细分 scenario tools, can jointly drive the precision and engineering implementation of agents. Second, the leap from single-agent execution to cluster collaboration is becoming more prominent. Multi-agent systems significantly enhance collective intelligence levels and multi-objective execution capabilities in complex research tasks through role division, information sharing, and task graph mechanisms, building more resilient and elastic research support networks. Third, human-machine collaboration is deepening and becoming multi-layered. Agents play diverse roles at different levels, achieving human-machine division of labor and complementarity from auxiliary retrieval to scientific hypothesis co-creation. Agents at all levels demonstrate closer and more flexible collaboration patterns with human users, becoming "intelligent partners" in research exploration. Finally, the preliminary formation of closed-loop capabilities has been verified in some systems. Despite challenges in generalization and stability, closed-loop exploration agents already possess prototype capabilities of "scientist-type" agents in task self-driving, error repair, and strategy evolution, 预示 new forms of research knowledge discovery and complex task support systems.

In summary, the diverse application pathways and capability accumulation of agent technology in complex task scenarios such as scientific research not only lay the technical foundation for "DIS Agents" but also provide solid practical support for analyzing the morphological characteristics of DIS Agents and the reshaping of intelligence work modes.

4 Transformation of S&T Intelligence Work Paradigm: Toward the DIS Agent Era

With the accelerated development of agent technology and its increasingly rich practical applications, intelligence work faces profound transformation opportunities and challenges. This chapter focuses on the theoretical and practical evolution of intelligence science, systematically analyzing the transformation logic and morphological evolution of intelligence work driven by agent technology.

4.1 Theoretical Foundation for Intelligence Work Paradigm Transformation

Intelligence, as a problem-oriented cognitive product, differs from general information in its timeliness, relevance, and decision-making value[49]. With the empowerment of new technologies, these characteristics of intelligence work have become more prominent, accelerating the evolution of intelligence services toward intelligent and cognitive directions.

The development of intelligence science has formed three parallel research paradigms: Information management-centered, focusing on systematic organization and equitable service of literature and data; Intelligence analysis-centered, emphasizing information integration analysis and strategic support; Communication and dissemination-centered, stressing the visibility and social diffusion of academic knowledge. These three paradigms have long coexisted. Driven by AI and agent technologies, they are evolving toward cross-domain integration, with fine-grained analysis orientation, problem orientation, and cognitive orientation as core concepts, guiding the construction of a DIKIW (Data-Information-Knowledge-Intelligence-Wisdom) based DIS Agent ecosystem[2, 3].

4.2 Challenges in AI-Driven Transformation of Intelligence Work

AI, particularly the rapid development of LLMs, is reshaping the technical system and organizational models of intelligence work. Intelligence agencies worldwide are actively exploring AI applications in information monitoring, semantic analysis, and trend forecasting. The U.S. Intelligence Advanced Research Projects Activity (IARPA) initiated the “FUSE”[50] and “SMART”[51] programs, validating AI’s capability boundaries in multi-modal intelligence reasoning and complex trend identification. The National Geospatial-Intelligence Agency (NGA) proposed the “GEOINT” AI strategy[52], emphasizing deep AI integration in geographic information interpretation and risk prediction. A joint report by the U.S. think tank “Special Competitive Studies Project” (SCSP) and the Australian Strategic Policy Institute (ASPI)[53] points out that future intelligence work will be dominated by “human-machine hybrid” models, with

AI playing core roles in anomaly detection and hypothesis generation. Global intelligence agencies are gradually moving from model fine-tuning and tool integration to organizational structure and talent system reconstruction, driving the intelligent transformation of intelligence work.

However, AI-driven intelligence systems still face numerous challenges, such as hallucination generation, semantic bias, lack of interpretability, and untraceable states, limiting their credibility in complex high-risk tasks[37]. In response, agencies worldwide have introduced explainable AI, responsibility attribution, and security protection systems to strengthen AI trustworthiness and human supervision. Overall, intelligence work is transforming from "human decision support" to "human-machine collaborative knowledge cognitive systems," laying a solid foundation for the development of DIS Agents.

4.3 Evolution of Intelligence Systems and Inevitability of Agent Transformation

Historically, intelligence systems have continuously evolved alongside technological innovation. In the Management Information Systems (MIS) stage, systems such as MEDLARS[54] and DIALOG information retrieval platforms centered on "literature retrieval-information management," building service models focused on information collection, storage, and retrieval. During this period, systems were highly integrated with relatively single functions, and intelligence workers were the dominators of information integration and retrieval.

In the Intelligence Systems (IS) stage, intelligence work shifted from static information retrieval to dynamic intelligence analysis and strategic support, forming an analytical work mode of "intelligence analysis-trend prediction-decision support." Systems like decision support systems and various intelligence analysis platforms emphasized information integration analysis and problem-oriented deduction. However, IS systems still maintained integrated, closed structures with highly coupled modules, unable to flexibly adapt and freely reconstruct like "agent genes" that could be flexibly embedded and dynamically combined across different tasks to form self-adaptive multi-agent systems.

Currently, with the deep integration of LLMs and agent technology, intelligence systems are advancing toward a new stage of intelligent decision-making characterized by "intelligentization-cognitization-taskization." DIS Agents, supported by multi-modal perception, process-driven execution, and multi-agent cluster collaboration, possess modular "agent gene"-like flexible assembly and task adaptation capabilities. This new form not only enables agents to achieve broad adaptability across modalities and tasks but also endows each module with "holistic intelligence" at the "partial" level, breaking through the rigid constraints of traditional IS systems.

More critically, in DIS Agent systems, the role of intelligence workers has also transformed: from single dominators of the full process to "task intention definers" and "process quality supervisors." They no longer focus on operational aspects of information collection and analysis but instead determine task objectives and quality standards, driving intelligence work to unfold efficiently, accurately, and dynamically through interaction and feedback with multi-agent clusters, forming a new human-machine synergy model. Figure 3 [Figure 3: see original paper] intuitively presents the evolution of intelligence systems and work modes from MIS and IS to DIS Agents, revealing fundamental differences in system architecture, intelligence levels, and human-machine collaboration methods across different stages.

Figure 3 Evolution of Intelligence Systems and Work Modes

Overall, intelligence systems are leaping from "information management" to "autonomous cognition," driving the intelligence system to evolve from closed, literature-based forms toward flexible, adaptive, and proactive multi-agent cluster application forms. This is not only a natural continuation of technological evolution but also an inevitable trend of generational leap, 预示 that intelligence work will naturally transition to the "DIS Agent era"[3]. Looking ahead, intelligence systems will build an Agentic AI application ecosystem based on the DIS Agent ecology, with autonomous capabilities and intelligent evolution potential, boosting the transformation of intelligence work modes from "static integration-single point analysis" to "dynamic cognition-intelligent collaboration."

4.4 Core Characteristics of DIS Agents and Reshaping of Intelligence Work Modes

DIS Agents are not merely an extension of the technical system for intelligence work but represent a brand-new "new paradigm of S&T documentation and information service." The core characteristics of this paradigm are manifested in three major aspects:

First, "agent gene"-like flexible composition and dynamic adaptation. DIS Agents break free from the closed integration limitations of past MIS and IS stages, achieving modular "agent gene"-like flexible composition. They can autonomously generate, dynamically adapt, and self-regulate in multi-modal perception, task planning, tool invocation, and other aspects, enabling intelligence services to possess broad adaptability across modalities and tasks.

Second, deep collaboration and elastic organization of multi-agent clusters. DIS Agents emphasize collective intelligence and collaboration mechanisms, forming flexible and reconstructible intelligence agent clusters through deep coupling of multi-agents in role division, semantic sharing, and strategy self-adaptation. This group-based, clustered intelligent system enables intelligence work modes to leap from "single-point-tool coupling" to "multi-agent-intelligent collaboration," possessing higher system elasticity and intelligence levels.

More importantly, the paradigmatic reshaping of intelligence workers' roles. In the DIS Agent stage, intelligence workers have transformed from information integrators in MIS and analysis dominators in IS to "task intention definers" and "process quality supervisors." Their core responsibilities have shifted from specific information collection and analysis to macro guidance and strategic coupling of multi-agent collaborative systems, focusing on problem orientation, task objective setting, and final outcome quality control and comprehensive judgment.

Overall, this new paradigm can be defined as: a brand-new work mode that takes "multi-agent cluster collaboration" as technical support, "task-oriented cognitive service" as organizational core, and integrates "agent gene-like flexible composition" with "human-multi-agent synergy gains"[3]. It not only breaks through the rigid boundaries of traditional intelligence systems, achieving intelligent adaptation and closed-loop task execution for dynamic problems, but also strengthens the flexibility, generalization, and autonomous evolution capabilities of intelligence services, driving intelligence work from "information management platforms" to "knowledge cognitive platforms."

In the future, how to achieve optimal human-multi-agent collaboration under safe and controllable conditions, promote high-quality evolution and continuous adaptation of DIS Agents, will become key issues for the intelligent upgrading of intelligence work processes[2], also marking the fundamental transformation of the new paradigm of S&T documentation and information service from concept to practice.

5 Conclusion and Outlook

This paper systematically reviews the development trajectory and capability evolution of agent technology, clarifying its multi-dimensional adaptation paths and application trends in scientific research and intelligence fields. The analysis shows that the evolution of agents is not only reflected in the upgrading of technical systems but also in their demonstration of stronger autonomy and adaptability through capabilities such as multi-modal perception, dynamic planning, and multi-agent cluster collaboration, laying a transformative capability foundation for the new application form of DIS Agents. The emergence of DIS Agents represents not only an update of the technical system but also a fundamental leap of intelligence work from human-dominated information organization and analysis to a new paradigm of "task-oriented cognitive service-multi-agent cluster collaboration-human-machine integrated intelligent assistance."

Unlike the integrated, closed systems of the MIS and IS eras, DIS Agents take "agent gene-like" modular flexible composition as the core, enabling autonomous, dynamic intelligent adaptation in complex and changing application scenarios. Simultaneously, the role of intelligence workers has also transformed from operational levels of information to "task intention definers" and "process quality supervisors," further strengthening problem orientation and cognitive gains. This new paradigm not only improves the execution efficiency and task closed-loop capability of intelligence services but also reshapes the core competitiveness of S&T documentation and information service in the intelligent era.

Looking ahead, the rise of DIS Agents is not only a natural extension of AI technology development but also the core driving force for reshaping the intelligence work system and achieving cross-generational leaps. How to achieve optimal human-multi-agent collaboration under safe and controllable conditions, continuously optimize multi-agent cluster capabilities, and improve cross-domain generalization levels will be key issues for the high-quality implementation and intelligent upgrading of DIS Agents. It is foreseeable that the widespread application and continuous evolution of DIS Agents will provide stronger intelligent support for S&T documentation and information service, driving it to continuously advance from "tool coupling" to a new stage of "intelligent collaboration."

Author Contributions: LIU Xiwen proposed research questions and content, designed the research framework, and wrote, revised, and finalized the paper. SUN Mengge wrote and revised the paper. FU Yun designed the research framework, conceived, wrote, revised, and finalized the paper.

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Note: Figure translations are in progress. See original paper for figures.