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AI-to-AI Communication: Toward a New Paradigm of Intelligence Search

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AI-to-AI Communication: Toward a New Paradigm of Intelligence Search

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Abstract

The rapid development of artificial intelligence has transformed the way people search for and interact with information. Traditional search engines primarily retrieve documents, web pages, and other information sources, while modern large language models can interpret questions, reason over information, and generate answers. This paper explores a possible next step: a search paradigm in which AI agents communicate with one another to search for, compare, evaluate, and synthesize answers.

This paper proposes an AI-to-AI communication paradigm for intelligence search, extending information retrieval beyond the conventional interaction between a user and a single AI model to a collaborative process involving multiple specialized AI systems. Rather than merely collecting or aggregating their responses, the framework enables participating systems to independently investigate a query, retrieve relevant evidence, exchange findings, and critically assess one another's contributions. The resulting intelligence is evaluated and integrated to construct a well-supported response.

A key distinction of the proposed architecture is its shift from answer-level agreement to claim-level verification. Instead of treating each AI-generated response as a single unit, the architecture decomposes responses into individual claims, independently retrieves supporting evidence, evaluates source independence, and accounts for dependencies among potential errors. This process enables the final synthesis to consider not only the agreement among AI systems but also the evidential support, credibility, and potential dependence underlying their claims.

The numerical results provide initial evidence that the proposed framework can support a new architectural layer between AI systems, dedicated to discovering, coordinating, evaluating, and verifying distributed machine intelligence. By enabling structured interaction and evidence-based assessment across multiple AI systems, this layer offers a foundation for moving beyond isolated AI capabilities toward more coordinated and reliable forms of machine intelligence.

This paper proposes an AI-to-AI communication paradigm for intelligence search, extending information retrieval beyond the conventional interaction between a user and a single AI model to a collaborative process involving multiple specialized AI systems.

Keywords

AI-to-AI communication; Intelligence search; AI agents; multi-agent systems; Collaborative Intelligence

1 Introduction

For decades, information search has followed a relatively straightforward paradigm: a user submits a query, a search engine retrieves relevant information from a collection of sources, and the system returns documents or web pages that may contain the desired answer. Although this paradigm has evolved considerably, its fundamental objective has largely remained the same: helping users locate relevant information.

The emergence of large language models (LLMs) marked a significant shift in this landscape. Rather than simply retrieving information, these models can interpret natural-language queries, leverage knowledge encoded in their parameters, reason about problems, and generate comprehensive responses. Nevertheless, their reliance on internal model knowledge introduces limitations, including incomplete knowledge and the generation of inaccurate or unsupported claims [1, 2]. Retrieval-augmented generation (RAG) addresses part of this challenge by connecting language-model generation with external information sources [3].

In parallel, research has increasingly moved toward more interactive and collaborative forms of artificial intelligence. Approaches such as ReAct combine reasoning with actions and interactions with external environments and information sources [4], while frameworks such as AutoGen demonstrate how multiple language-model-based agents can communicate and collaborate to accomplish complex tasks [5]. These developments have expanded the role of AI systems from standalone answer generators to interactive entities capable of using tools, exchanging information, and coordinating task execution.

Figure 1 illustrates this broader technological evolution, from keyword-based and semantic search to generative and retrieval-enhanced systems, followed by agentic and intelligent search approaches.

These developments open a new perspective on the evolution of search: rather than limiting the search space to documents, databases, and other information sources, search could extend to the AI systems themselves as sources of knowledge, reasoning, and evidence. This perspective underlies the concept of AI-to-AI Communication for Intelligence Search, which reframes search as the discovery and evaluation of intelligence distributed across multiple artificial intelligence systems.

Within this paradigm, a coordinating system can engage heterogeneous AI models and specialized agents to examine a query from different perspectives. Their outputs are not treated as equally reliable or simply combined through response aggregation. Instead, the architecture supports comparative assessment, disagreement identification, evidence-based verification, and selective synthesis. This process makes the quality of the final response dependent not merely on the number of participating systems or their degree of agreement, but also on the relevance and credibility of their contributions and the potential dependencies among their errors.

Several established research directions provide complementary foundations for this vision, although they address different aspects of the problem. Retrieval-augmented generation (RAG) connects language-model generation with external information retrieval; agentic approaches emphasize autonomous planning and tool use; multi-agent systems investigate coordination among multiple agents; model routing focuses on selecting appropriate models for specific tasks; and agent discovery addresses the identification of relevant agents within an ecosystem. More recently, multi-LLM collaborative search has explored cooperation among multiple language models for complex search and reasoning tasks, with approaches such as MOSA demonstrating the potential of iterative collaboration [3–10].

The research gap addressed in this work is primarily conceptual rather than technological: although existing approaches provide capabilities for information retrieval, agent coordination, model selection, and collaborative reasoning, they do not necessarily frame these capabilities within a unified search process centered on discovering and evaluating task-relevant intelligence across heterogeneous AI systems. To address this gap, this paper proposes an integrated perspective in which a coordinating system identifies relevant AI systems, establishes communication with selected participants, evaluates their contributions through evidence-based assessment, and synthesizes the resulting intelligence into a coherent response.

The remainder of this paper is organized as follows. Section 2 discusses the transition from information search to intelligence search. Section 3 presents the proposed AI-to-AI Communication framework and its overall architecture. The simulation methodology and evaluation results are presented in Section 4. Finally, Section 5 discusses the findings, limitations, and implications of the proposed approach, while Section 6 concludes the paper and outlines directions for future research.

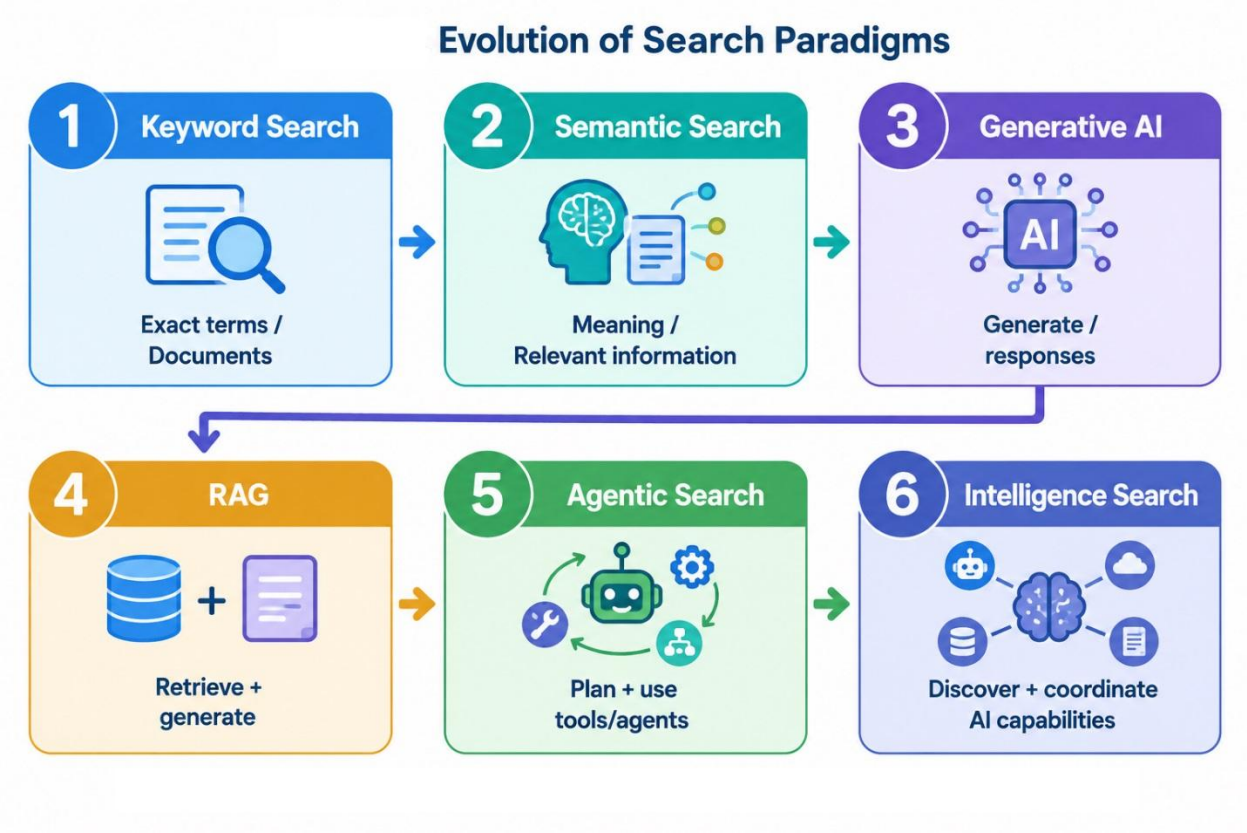


Figure 1. Evolution of Search Paradigms.

2 From Information Search to Intelligence Search

Figure 2 illustrates the conceptual transition from conventional information search to intelligence search. Although both paradigms aim to address user needs, they differ in their search objectives, target resources, and operational processes. Conventional information search primarily receives a query and retrieves relevant information objects from available collections. In contrast, intelligence search starts with a task, goal, or problem, potentially accompanied by constraints such as required expertise, reliability, latency, cost, and available tools. Consequently, the search objective shifts from finding relevant information to identifying and coordinating the artificial intelligence capabilities required to accomplish a given task.

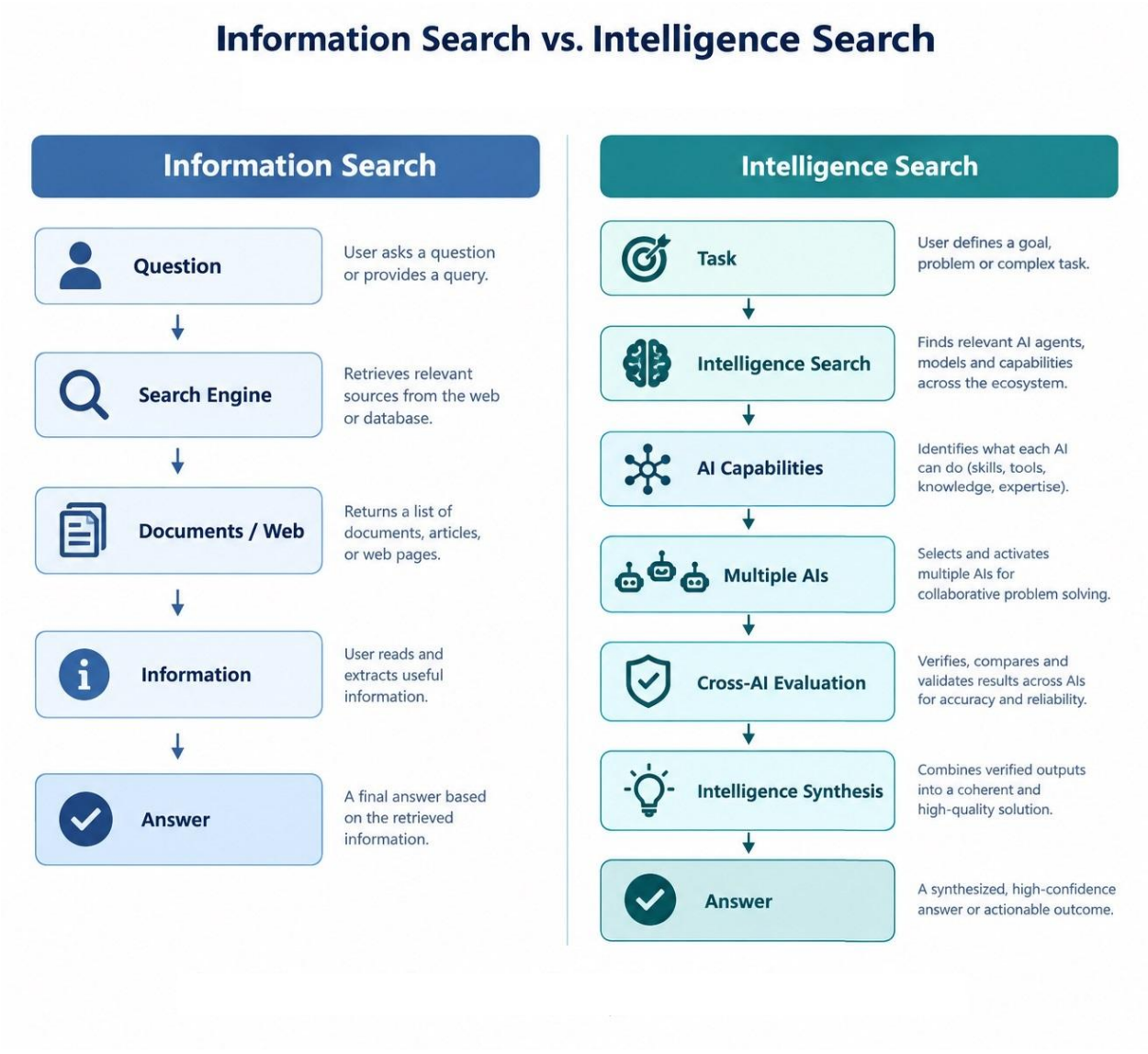


Figure 2. Information Search versus Intelligence Search.

In conventional search environments, the searchable resources typically include documents, web pages, images, videos, databases, and other information repositories. Within an AI ecosystem, however, the available resources extend beyond information objects to include language models, specialized agents, reasoning modules, tool-enabled agents, simulators, and verification systems. These entities differ in their knowledge, capabilities, expertise, operational characteristics, and reliability. Therefore, identifying an appropriate resource requires considering not only its apparent relevance to a query but also its actual capabilities and suitability for the task.

From this perspective, the evolution toward intelligence search can be understood through three conceptual levels. Information Search, focuses on retrieving relevant information from available sources. Agent Search, extends the search space to artificial intelligence agents that can perform specific tasks or provide particular capabilities. Intelligence Search, however, goes beyond identifying individual agents and aims to discover, select, and coordinate the capabilities distributed across multiple AI systems. Depending on the nature of the task, this may involve selecting a single specialized model or forming a collaborative configuration of multiple heterogeneous agents. Thus, intelligence search is not necessarily equivalent to multi-agent execution; rather, it concerns identifying the most suitable available intelligence resources and determining how they should contribute to solving a problem.

An important distinction is that the relevance of an AI system to a task does not necessarily imply that its contribution will be accurate or useful. An agent may possess relevant expertise while producing incomplete, outdated, or incorrect information. Similarly, multiple agents may provide apparently consistent responses without offering independent confirmation, particularly when they share similar knowledge sources, model architectures, or underlying biases. Consequently, intelligence search requires more than capability matching or response aggregation. It also involves assessing the quality and relevance of the contributions, examining the supporting evidence, identifying disagreements, and considering potential dependencies among participating systems.

Another important aspect concerns the dynamic nature of intelligence selection. The most suitable configuration of AI systems may depend on the task requirements, the information obtained during execution, and the observed performance of participating agents. An initially selected agent may prove insufficient as the task progresses, while additional expertise or independent verification may become necessary. Accordingly, intelligence search can be viewed as a potentially iterative process in which the selection and coordination of AI capabilities may be revised in response to emerging evidence and evaluation outcomes.

Taken together, these considerations establish a broader conceptual foundation for AI-to-AI Communication as an intelligence search paradigm. In this perspective, artificial intelligence systems are not merely endpoints that generate independent responses, nor are they simply interchangeable information sources. They constitute a distributed pool of computational and reasoning capabilities that can be discovered, accessed, evaluated, and coordinated according to task requirements. The central objective is therefore not to maximize the number of participating models or agents, but to identify and organize the combination of

capabilities that can provide the most reliable and relevant solution to the problem at hand. This perspective provides the conceptual basis for the framework introduced in the following sections.

3 Proposed Architecture

Figure 3 illustrates the overall architecture of the proposed framework, encompassing the interrelated stages of intelligence acquisition, agent coordination, and response generation. A user task is first mapped to a required intelligence profile, which guides the discovery and selection of suitable AI agents through Intelligence Search. The selected agents subsequently engage in coordinated communication and collaboration, with their outputs subjected to agreement and conflict analysis before being integrated into a final response. The architecture further incorporates feedback pathways, allowing information derived from intermediate evaluations to influence preceding stages and facilitate adaptive adjustments throughout the process.

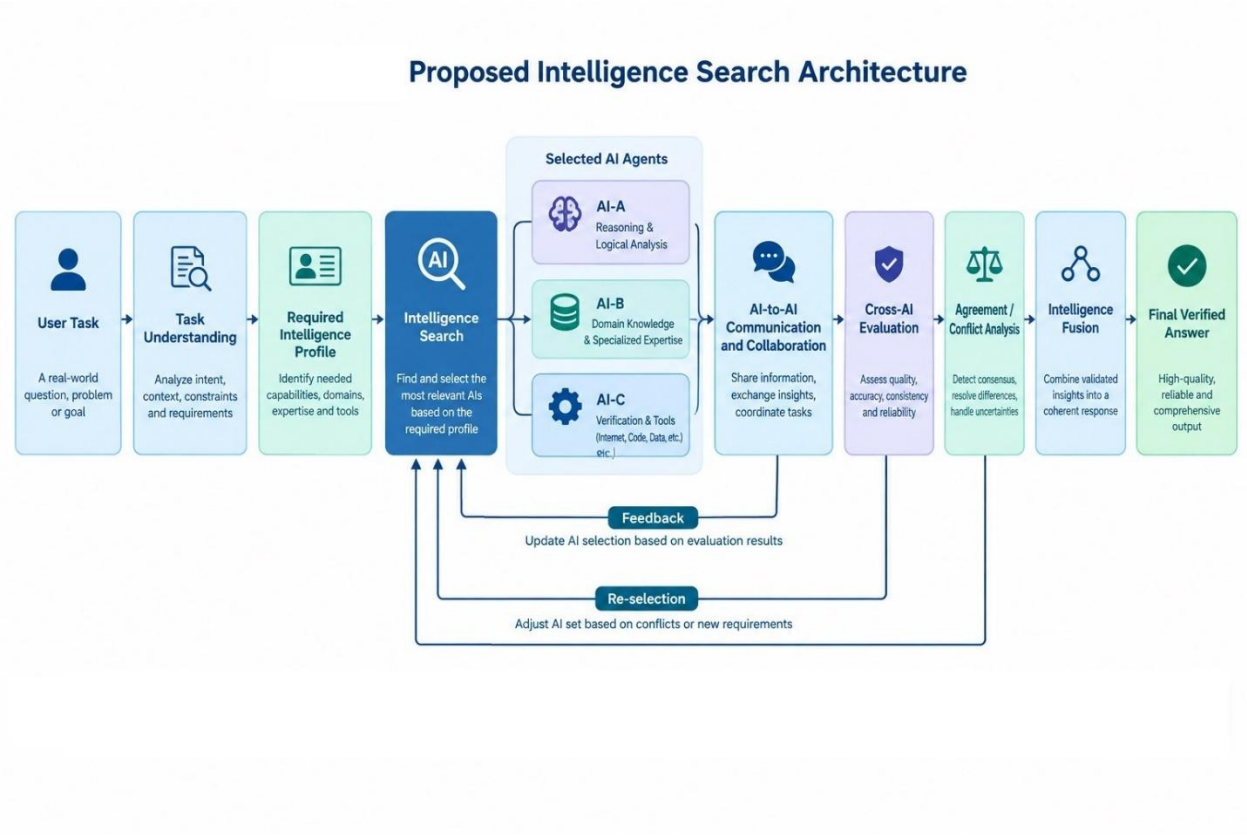


Figure 3. Proposed Intelligence Search Architecture.

3.1 Task Understanding

The system first analyzes the task to identify its intent, complexity, constraints, and expected output. This analysis establishes an understanding of the problem and the different forms of intelligence that may be involved in addressing it.

3.2 Required Intelligence Profile

Based on the task analysis, the system constructs a required intelligence profile specifying the capabilities, domain expertise, and resources needed to address the task. This profile may also define tool requirements, reliability targets, cost limits, response-time constraints, and the desired degree of independent verification. It then serves as the query for the Intelligence Search layer.

3.3 AI Capability Discovery

The Intelligence Search layer is responsible for discovering, evaluating, ranking, and selecting AI agents according to their capabilities and suitability for the target task. Candidate agents may include general-purpose LLM-based agents, domain-specific AI agents, tool-enabled agents, retrieval agents, and verification agents. The discovery process may draw on system metadata, historical performance, execution tests, reputation, and task-specific evidence.

Candidate agents are ranked according to a set of task-dependent criteria. A conceptual scoring function can be expressed as:

$$Score(AI_i, T) = w_c C_i + w_q Q_i + w_r R_i + w_t T_i - w_k K_i$$

where C represents capability match, Q represents expected quality, R represents reliability, T represents time efficiency, and K represents cost, for candidate agent (i). The corresponding weights determine the relative contribution of each criterion to the selection process, according to the requirements of the target task. This formulation frames agent selection as a multi-objective retrieval problem while remaining independent of any specific ranking or optimization algorithm.

Beyond initial discovery and selection, the Intelligence Search layer serves as the adaptive decision-making component of the architecture. It integrates feedback from AI-to-AI Communication, Cross-AI Evaluation, and Agreement–Conflict Analysis to reassess candidate agents, refine their rankings, and determine whether agent replacement or team reconfiguration is necessary. Through this feedback-driven process, the composition of the agent team can be dynamically adjusted in response to communication outcomes, evaluation evidence, and identified agreement or conflict patterns.

3.4 AI-to-AI Communication

Following agent selection, AI-to-AI communication establishes the interaction mechanisms through which the selected agents coordinate their activities and contribute to a shared task. These interactions encompass task decomposition, assignment and coordination of subtasks,

exchange of information and intermediate results, and the provision of task-related requests and responses. Through these exchanges, individual AI agents can build upon one another's contributions, exploit complementary capabilities, and coordinate their respective roles in addressing the user's task. Communication thus provides the operational foundation for collaboration among distributed AI agents, enabling them to combine their individual capabilities within a unified intelligence-seeking process.

3.5 Cross-AI Evaluation

The outputs generated by participating AI agents are systematically evaluated before being integrated into the final response. Cross-AI Evaluation examines the quality and credibility of individual contributions by considering factors such as supporting evidence, reasoning validity, consistency, tool-derived results, and independent verification signals. This assessment helps distinguish well-supported contributions from potentially unreliable or insufficiently substantiated outputs. The resulting evaluation information is subsequently used in the Agreement–Conflict Analysis stage to assess the relationships among the contributions of different AI agents. Evaluation findings may also provide feedback to the Intelligence Search process when the quality or reliability of the available contributions indicates the need for further agent discovery or selection.

3.6 Agreement-Conflict Analysis

The Agreement–Conflict Analysis block examines the relationships among evaluated AI outputs to identify areas of agreement, complementary contributions, and substantive contradictions. Agreement among independently supported outputs can strengthen confidence in the corresponding conclusions, whereas significant conflicts may indicate unresolved uncertainty, insufficient evidence, or limitations in the participating agent set. Depending on the nature and significance of these conflicts, feedback can be directed to the Intelligence Search stage to reassess the current agent configuration and, where necessary, identify alternative or additional AI agents. The updated configuration can then re-enter the collaborative process for further information exchange and evaluation. This feedback mechanism enables the proposed architecture to adapt its agent composition in response to the outcomes of cross-AI analysis rather than relying on a fixed, linear processing sequence.

3.7 Intelligence Synthesis

The Intelligence Fusion module consolidates the evaluated outputs of the preceding stages into a unified intelligence representation. By integrating complementary information and resolving inconsistencies based on the preceding evidence and evaluation results, it produces a coherent and reliable output. This consolidated output is then directly forwarded to the Final Answer module for response generation.

4. Simulation Setup and Performance Evaluation

To investigate the potential benefits of the proposed Intelligence Search framework, the proposed structure was evaluated under a simple simulation scenario implemented in Python. The simulation scenario involved 12 synthetic AI agents with different capability, response-quality, reliability, response-time, and cost

characteristics. Agent characteristics are randomly generated within predefined ranges. The main simulation parameters are summarized in Table 1.

Table 1. Simulation parameters and configuration

Value	Parameter	Value	Parameter
2,000	Number of tasks	12	Number of agents
3	Initial selected agents	3	Number of domains
3	Maximum feedback rounds	5	Maximum selected agents
0.35–1.00	Capability range	0–0.75	Correlation range
0.65–0.99	Reliability range	0.65–0.98	Quality range
0.1–1.0	Cost range	0.5–5.0	Response-time range

Three configurations were evaluated: (i) Single AI, in which the highest-ranked agent independently generates the response to each task; (ii) Basic Multi-AI, which combines the responses of the three highest-ranked agents using majority voting; and (iii) the proposed Adaptive Intelligence Search approach. In the proposed adaptive approach, the system initially selects three agents and dynamically expands the team to a maximum of five agents whenever the response agreement falls below 0.75. Additional agents are selected based on their suitability, with preference given to agents belonging to different groups to promote diversity. The final answer is determined through majority voting, while the highest-ranked response is used to resolve ties.

Fig. 4 compares the answer accuracy of Single AI, Basic Multi-AI, and the proposed Intelligence Search approach under different levels of latent Gaussian correlation. The dependence among agents is controlled through a Gaussian copula, where the correlation parameter (ρ \rho) determines the strength of dependence in the underlying latent variables. The results are averaged over 50 independent random seeds, with 95% confidence intervals.

The three configurations exhibit different responses to increasing latent correlation. Single AI maintains an almost constant accuracy across all tested correlation levels, as its performance is independent of inter-agent dependence. In contrast, Basic Multi-AI shows a gradual decline in accuracy as the latent correlation increases. This indicates that the benefits of conventional multi-agent collaboration are sensitive to the dependence structure among agents, with stronger dependence reducing the accuracy gains achieved through collaboration.

The proposed Intelligence Search approach achieves the highest accuracy at every tested correlation level. Although its accuracy also decreases as latent correlation increases, it maintains a clear advantage over both baselines throughout the experiment.

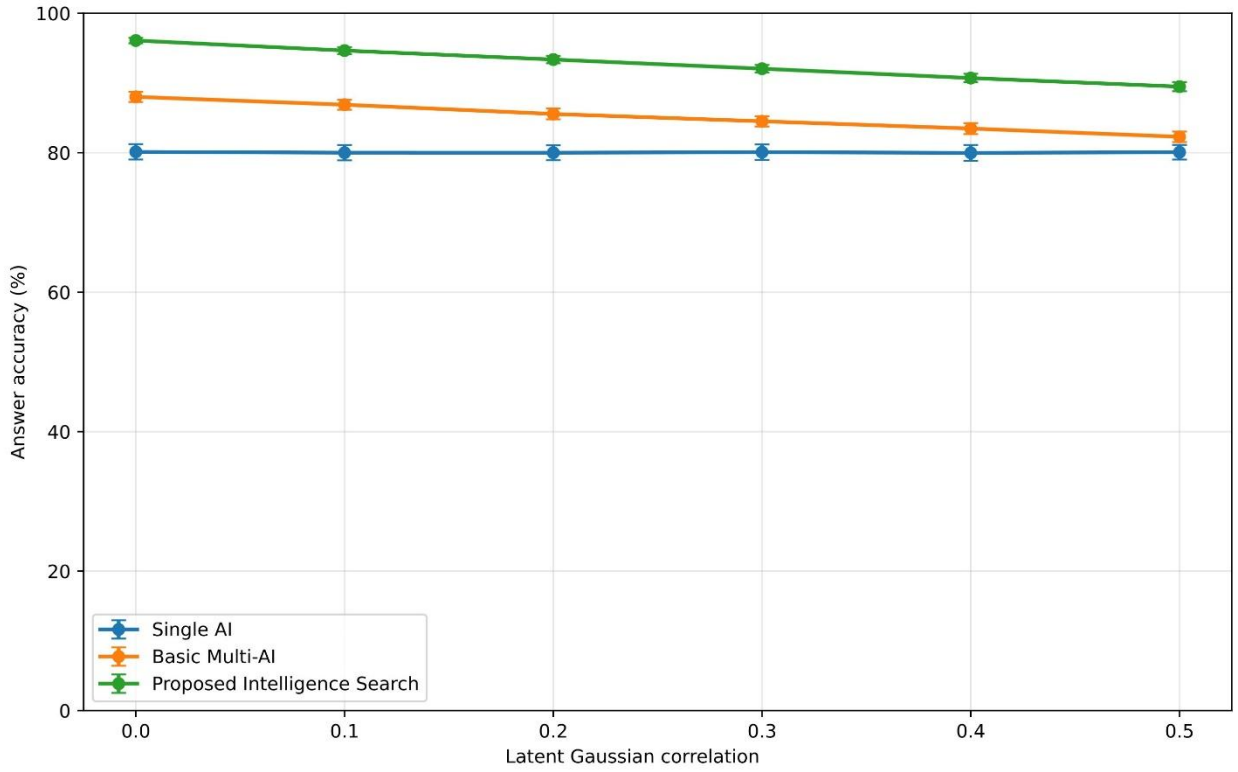


Figure 4. Answer accuracy versus Gaussian-Copula correlation

The consistent performance advantage observed across all investigated correlation levels provides encouraging preliminary evidence of the effectiveness of the proposed approach. Although its generalizability remains to be examined under a broader range of experimental conditions and more complex multi-agent scenarios, the improvements achieved in this study highlight its potential as a promising direction for advancing adaptive intelligence search. These findings provide a solid motivation for continued investigation into more effective and reliable AI-to-AI communication and collaborative intelligence mechanisms.

5. Discussion

This paper proposes an adaptive framework for intelligent search in which AI systems are dynamically discovered, selected, and coordinated according to the requirements of a given task. Unlike conventional search approaches that primarily retrieve information, the proposed framework treats AI agents themselves as searchable and selectable sources of intelligence. By adapting the participating agents and evaluating their contributions throughout the search process, it aims to move beyond information retrieval toward intelligence retrieval, where the objective is not simply to find relevant information, but to identify and combine the most suitable AI capabilities to address a task.

The simulation results offer encouraging evidence for the effectiveness of this perspective. They indicate that structured interaction among multiple AI agents, combined with appropriate agent selection and adaptive coordination, can improve search outcomes compared with conventional and less coordinated approaches.

Importantly, these improvements do not arise simply from increasing the number of participating models. Rather, they underscore the importance of identifying suitable agents and effectively integrating their contributions into a coherent search process.

An important aspect of the proposed framework is its compatibility with emerging agent communication standards. For example, the Agent2Agent (A2A) protocol could provide a complementary mechanism for agent discovery and interoperability [11]. However, the contribution of the proposed framework extends beyond communication itself. Its central concern is how discovered agents are selected, coordinated, and evaluated to obtain a more suitable answer. This distinction allows the framework to remain independent of any particular communication protocol while benefiting from standardized agent interaction.

The proposed approach also differs fundamentally from the objective of Artificial General Intelligence (AGI). While AGI seeks to develop broadly capable individual systems [12], this framework explores how existing specialized AI systems can collectively address tasks through structured interaction. Its emphasis is therefore not on creating a single more capable model, but on exploiting distributed and potentially complementary intelligence. In this sense, intelligent search offers a complementary direction in the evolution of AI systems.

Despite its potential, practical deployment presents challenges. Coordinating multiple systems may introduce additional computational overhead and response latency, while heterogeneous capabilities, access conditions, and communication interfaces may complicate integration. These considerations make efficient agent selection and coordination essential to the scalability of the approach.

Overall, the simulation findings provide encouraging support for the proposed framework and its potential to advance intelligent search. Beyond the retrieval of information, such an approach could enable more systematic exploration of complex questions, support scientific discovery, and improve problem-solving in domains where no single AI system may provide the most suitable response. Further evaluation across diverse tasks and real-world environments will be necessary to establish the generality and practical impact of this paradigm.

6. Conclusion

This article introduced Intelligence Search as a perspective on the future of AI-enabled search and proposed an adaptive framework to explore its realization through AI-to-AI Communication. The simulation study provides initial evidence of the framework's potential to improve search effectiveness, supporting the feasibility of moving beyond conventional information-oriented approaches.

The contribution of this work lies not in presenting agent discovery, multi-agent collaboration, or AI communication as isolated innovations, but in bringing them together within an adaptive search architecture. This perspective places the selection and use of AI capabilities at the center of the search process and opens a broader research direction in which intelligence itself becomes the object of search.

Realizing this vision will require further investigation across diverse tasks, heterogeneous AI ecosystems, and practical deployment settings. Nevertheless, the proposed framework offers a foundation for exploring a

different role for search systems: not merely retrieving what is already available, but identifying the intelligence needed to address what is being asked.

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Data Availability

The data supporting the findings of this study, including the simulation results, are available from the corresponding author upon reasonable request.

Author Contributions

Hamid Shahrokh Shahraki conceptualized the research, developed the proposed architecture and methodology, designed and implemented the simulation framework, performed the analysis, interpreted the results, and wrote and revised the manuscript.

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