# From Web Search towards Agentic Deep Research: Incentivizing Search with Reasoning Agents

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#### **Abstract**

Information retrieval is a cornerstone of modern knowledge acquisition, enabling billions of queries each day across diverse domains. However, traditional keywordbased search engines are increasingly inadequate for handling complex, multi-step information needs. Our position is that Large Language Models (LLMs), endowed with reasoning and agentic capabilities, are ushering in a new paradigm termed Agentic Deep Research. These systems transcend conventional information search techniques by tightly integrating autonomous reasoning, iterative retrieval, and information synthesis into a dynamic feedback loop. We trace the evolution from static web search to interactive, agent-based systems that plan, explore, and learn. We also introduce a test-time scaling law to formalize the impact of computational depth on reasoning and search. Supported by benchmark results and the rise of open-source implementations, we demonstrate that Agentic Deep Research not only significantly outperforms existing approaches, but is also poised to become the dominant paradigm for future information seeking. All the related resources, including industry products, research papers, benchmark datasets, and open-source implementations, are collected for the community in https://github.com/ DavidZWZ/Awesome-Deep-Research.

#### 1 Introduction

"Introducing deep research: An agent that uses reasoning to synthesize large amounts of online information and complete multi-step research tasks for you."

- OpenAI

Every day, billions of people search for information online (Amendola et al., 2023), and rely heavily on these online resources to make decisions across personal, professional, and societal contexts (Zhang et al., 2024a). For decades, traditional web search engines based on keyword matching have served as the primary gateway to digital information. While once revolutionary, these

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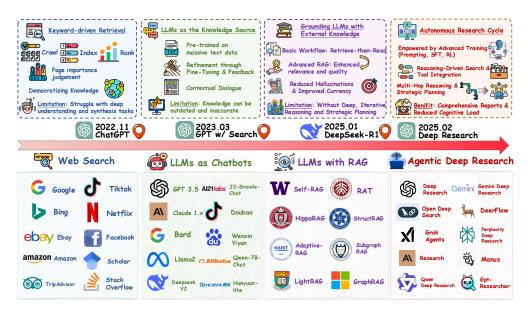


Figure 1: The evolution of information search paradigms.

systems increasingly struggle with complex, multi-faceted queries that demand nuanced understanding and synthesis (Mo et al., 2024). The growing inadequacy highlights their inherent limitations in contextual comprehension and knowledge integration.

Against this backdrop, information seeking and synthesis are undergoing a profound transformation with large language models (LLMs). Rather than merely enhancing traditional search paradigms, LLMs are poised to fundamentally replace them in addressing complex information needs. Initially, we witnessed the rise of LLMs as standalone, knowledgeable chatbots, which challenged the dominance of web search by offering more direct answers and a degree of synthesis, thereby reducing the user's burden of sifting through numerous links (Liu et al., 2023). However, single LLMs are tethered to static, offline knowledge. The subsequent integration of search and retrieval-augmented generation (RAG) marked a step forward, grounding LLMs in external data and mitigating issues like hallucination (Ma et al., 2023; Yang et al., 2025). Nevertheless, these naive RAG methods still struggle with real-world questions that require sophisticated multi-hop reasoning and strategic search planning, as they often cannot plan correct search paths for complex problems (Yao et al., 2023b).

Recently, test-time scaling (TTS) has emerged as a potent paradigm for boosting the reasoning and agentic capabilities of LLMs (Snell et al., 2024). It assigns additional computation during inference, enabling deeper problem-solving (Zou et al., 2025a; Gu et al., 2025). Equipped with TTS on reasoning and search, LLMs are set to drive a new search paradigm termed **Agentic Deep Research** systems, which are capable of autonomous **reasoning**, on-demand **searching**, and iterative information synthesis. Demonstrations from deep research products launched by OpenAI and Google highlight several key advantages of this paradigm: (1) Comprehensive Understanding: Ability to dissect and address complex, multifaceted queries that overwhelm traditional methods (Wei et al., 2022); (2) Enhanced Synthesis: Excels at synthesizing information from diverse, potentially conflicting sources into coherent and insightful narratives (Cheng et al., 2025); (3) Reduced User Burden: Significantly decreases the cognitive load and manual effort required from users by automating laborious search steps (Sami et al., 2024).

Our position is that the LLM-driven Agentic Deep Research framework will inevitably become the dominant paradigm for future information search. In this paper, we comprehensively investigate this paradigm shift and make four key contributions: (1) We systematically trace and analyze the evolutionary trajectory of information search paradigms, from traditional keyword-based search, through conversational LLM chatbots and naive search-augmented LLMs, and ultimately to the Agentic Deep Research; (2) We introduce the test-time scaling (TTS) law for Deep Research, a novel hypothesis formalizing the relationship between inference-time computational resources allocation and the resulting improvements in LLMs reasoning capabilities and knowledge depth; (3) We conduct extensive evaluations on existing Agentic Deep Research models, coupled with analyses of open-

source implementations to support our position; and (4) As the first to holistically summarize the field of Deep Research, we offer a detailed exploration of critical future research directions, outlining both opportunities and challenges. Our discussion outlines a clear roadmap for this rapidly evolving field, underscoring how this evolution is fundamentally reshaping human interaction with real-world information and guiding further advancement on Agentic Deep Research.

# 2 Traditional Information Search Paradigms

The evolution of search paradigms as in Figure 1 represents a fundamental transformation in how humans access and interact with information. This section examines three distinct frameworks that have shaped the landscape of information retrieval: traditional web search engines, Large Language Models (LLMs) as chatbots, and LLMs with Retrieval Augmented Generation (RAG) systems. Each paradigm offers unique capabilities and addresses prior information seeking challenges, from systematic web crawling and ranking to interactive dialogue and knowledge-augmented generation.

#### 2.1 Web Search

Web search has fundamentally transformed information access in modern society, enabling near-instantaneous retrieval of knowledge that previously required days or months to locate (Brin and Page, 1998). This revolutionary technology has democratized knowledge acquisition, accelerated economic development through improved information flow, and catalyzed scientific discovery by providing researchers with rapid access to cutting-edge developments. As the primary infrastructure for information retrieval in the Internet era, online search engines like Google have continuously shaped how humans interact with the expanding information landscape (Page et al., 1999).

The applications of web search span diverse contexts, from general-purpose engines handling broad information needs to specialized platforms optimized for specific domains. General search engines utilize sophisticated algorithms to address multifaceted user queries (Broder, 2002), while specialized systems like Google Scholar focus on academic literature, providing researchers with precise pathways to scholarly resources (Noruzi, 2005). Content platforms (TikTok), social networks (Facebook), and e-commerce sites have developed internal search capabilities tailored to their unique content types and user behaviors, demonstrating how web search has permeated virtually every digital sphere.

Basically, web search operates through three fundamental processes: crawling (Khder, 2021), indexing (Hendriksen et al., 2024), and ranking (Robertson et al., 2009). Crawlers systematically discover and collect web content, which is then analyzed and organized into inverted indices for efficient retrieval. When users submit queries, search engines employ complex algorithms to assess document relevance and importance (Fuhr, 1992). The PageRank algorithm revolutionized search by evaluating page authority based on the web's citation graph, determining a page's significance through its incoming links from other high-quality pages (Page et al., 1999). Modern search systems have further evolved to incorporate semantic understanding, user behavior data, and personalization to deliver increasingly relevant results (Wang et al., 2024b). However, the contexts presented to the user may not always be relevant and accurate, due to the limited context for user-specific complex queries (Leake and Scherle, 2001) and the influence of advertisement bidding (Linden et al., 2009).

#### 2.2 LLMs as Chatbots

Leveraging recent advances in natural language processing (NLP) and hardware enhancements, large language models (LLMs) represent the latest evolution in information retrieval as user chatbots for tailored response generation. Models like ChatGPT Achiam et al. (2023), Claude Anthropic (2023), and LLaMa Touvron et al. (2023) transcend traditional static retrieval methods by engaging users through interactive dialogue with integrate and tailored solutions that not directly available online (Thirunavukarasu et al., 2023; Kasneci et al., 2023). Unlike conventional search engines that process each query independently—requiring iterative user efforts in providing contextual information and content browsing, LLM chatbots maintain conversation history throughout interactions, Beyond that, they aggregate vast amounts of web-sourced knowledge within their parameters, effectively serving as compact representations of extensive online information (Zhang et al., 2022; Zeng et al., 2022). Through supervised fine-tuning on conversation and instruction datasets (Iyer et al., 2022), coupled with reinforcement learning from human feedback (RLHF) (Bai et al., 2022), these models

optimize their responses for accuracy, relevance, and alignment with user preferences. Additionally, targeted prompt engineering (Zhou et al., 2022) and optimization techniques (Li and Liang, 2021), alongside maintaining conversational context (Callison-Burch et al., 2022), further enhance the coherence and maturity of multi-turn interactions.

However, despite these advantages, relying exclusively on internal LLM knowledge presents notable challenges: (1) *hallucinations*, where models generate plausible but inaccurate content (Tam et al., 2023; Yao et al., 2023a; Zhao et al., 2025); (2) *lack of awareness of recent events*, which compromises the timeliness of responses (Chen and Shu, 2023); and (3) *Limited context window*, hindering a comprehensive understanding of complex queries (Wang et al., 2024c). Therefore, integrating external information sources and employing advanced reasoning to verify retrieved data are crucial strategies for addressing these limitations, thus ensuring LLM chatbots deliver accurate, relevant, and up-to-date information (Peng et al., 2023).

#### 2.3 LLMs with RAG

To address the inherent limitations of LLMs mentioned above, particularly their static knowledge and tendency to hallucinations, Retrieval Augmented Generation (RAG) has emerged as a promising paradigm (Prabhune and Berndt, 2024). RAG integrates the generative capabilities of LLMs with retrieval systems to dynamically access relevant external information. Early implementations of RAG primarily employed a straightforward "Retrieve-then-Read" workflow (Ma et al., 2023), typically involving a single-step retrieval from a predefined local database or document collection. Although they improve upon purely parametric methods, such naive RAG systems can still struggle with inaccurate retrieval when faced with complex queries.

To solve this problem, multi-hop retrieval addresses the limitations of traditional single-hop retrieval by enabling iterative, sequential searches and reasoning steps across multiple data sources (Jiang et al., 2023). Multi-hop retrieval incorporates iterative refinement, where intermediate retrieval outcomes guide subsequent queries, progressively building comprehensive context (Zhang et al., 2025a). Although multi-hop retrieval has strong power generation capabilities, it also suffers from limitations due to the underlying techniques it employs. Early stage errors in reasoning paths can propagate throughout subsequent retrieval and reasoning steps, severely influencing the final output integrity (Zhang et al., 2025a). Additionally, maintaining faithfulness to retrieved evidence poses ongoing difficulties, as language models frequently encounter conflicts between retrieved data and internal parametric knowledge (Zheng et al., 2025b).

# 3 Towards Agentic Deep Research

Many complex real-world problems, including open-domain question answering (Yang et al., 2015; Chen and Yih, 2020) and scientific discovery (Lu et al., 2024; Wang et al., 2023b; Baek et al., 2024; Schmidgall et al., 2025), inherently require an iterative interplay between information retrieval and reasoning. A single search step often falls short of capturing comprehensive information, while isolated reasoning phases can fail to identify critical insights (Trivedi et al., 2023). By tightly integrating search and reasoning in a multi-step and interactive manner, these systems can progressively enhance the relevance and depth of retrieved knowledge and simultaneously refine the reasoning process underlying query interpretation, ultimately producing more accurate and contextually nuanced responses. Here, reasoning actively influences search (e.g., refining search queries based on intermediate deductions), while retrieved information recursively refines reasoning in a dynamic feedback loop. Unlike the previous LLM with RAG framework in Section 2.3, where retrieval and reasoning occur in discrete and sequential stages, this approach treats them as interdependent, continuously co-evolving.

This evolution in search methodologies gives rise to a transformative paradigm we define as Agentic Deep Research. In this paradigm, language models takes on the role of active information-seeking agents. Rather than a one-shot prompt + retrieve paradigm, an "agentic" LLM plans a series of steps: it can issue search queries, consult documents, browse on web, or even collaborate with other agents, all while refining its query understanding and response via iterative retrieval and reasoning. Inspired by the way human experts might research a question, we encapsulate this iterative synergy between *reasoning* and *search* in the term **Deep Research** highlighting its dynamic and interactive essence. To substantiate our central position that LLM-driven Agentic Deep Research

will inevitably become the predominant paradigm for future information-seeking—we ground our argument across three interlinked technical dimensions: reasoning capabilities as the foundation, principled approaches to incentivize search, and ecosystem-level momentum evidenced through benchmarks and implementations.

The evolution of reasoning capabilities in large language models represents a crucial stepping stone toward truly agentic systems, particularly in the context of deep research tasks. While Chain-of-Thought (CoT) prompting (Wei et al., 2022) initially demonstrated the possibility of explicit reasoning processes, the real breakthrough lies in how reasoning mechanisms enable autonomous decision-making and strategic planning, essential for conducting deep research. The transformation from simple CoT to more sophisticated reasoning frameworks marks a fundamental shift in how AI systems approach complex tasks. Rather than merely following predetermined patterns, modern reasoning frameworks enable systems to dynamically plan, execute, and adjust their approach based on intermediate outcomes. This capability is particularly evident in recent reinforcement learning-based optimization approaches (Jaech et al., 2024; Guo et al., 2025), which have demonstrated unprecedented abilities in managing complex search tasks. These systems can autonomously determine when to initiate searches, formulate appropriate queries, and synthesize findings into coherent understanding, forming the cornerstone of agentic behavior.

The DeepSeek-R1 (Guo et al., 2025) represents a significant milestone in this evolution, demonstrating how reinforcement learning can optimize reasoning processes for complex mathematical tasks. By learning from experience and feedback, these systems develop sophisticated strategies for information gathering and synthesis, moving beyond simple pattern matching to true strategic planning. This advancement in reasoning capabilities provides the essential foundation for agentic deep research by enabling systems to autonomously evaluate information needs, strategically decompose complex queries, synthesize information across multiple sources while maintaining logical consistency, and adapt search strategies based on intermediate results and feedback (Jin et al., 2025). These capabilities, rooted in advanced reasoning mechanisms, establish the preliminary foundation necessary for conducting deep research tasks that require strategic planning, iterative refinement, and complex decision-making. The integration of reinforcement learning with reasoning frameworks represents a crucial step toward truly agentic systems capable of conducting sophisticated research autonomously, marking a significant advancement from traditional search and retrieval paradigms (Chen et al., 2025b).

#### 3.1 Incentivizing Search with Reasoning Agents

Within this paradigm, reasoning is not merely an auxiliary component applied post-retrieval; rather, it constitutes the core mechanism that determines when, what, and how to search (Wu et al., 2025). While prompting and supervised fine-tuning (SFT) serve as foundational techniques for instilling tool-use behaviors and basic query generation, they are inherently limited by their reliance on fixed instruction patterns and offline supervision (Wang et al., 2023a; Ghosh et al., 2024). In contrast, reinforcement learning (RL) provides a principled framework for cultivating truly agentic behavior—enabling models to explore, self-correct, and adaptively optimize their retrieval strategies in open-ended, interactive environments (Singh et al., 2025; Jin et al., 2025; Song et al., 2025). This shift toward RL-incentivized search marks a critical step toward developing autonomous agents capable of reasoning-driven information acquisition.

Prompting and In-Context Learning: Bridging Search and Reasoning. Prompting methods have laid important groundwork for coupling reasoning with external information retrieval. ReAct (Yao et al., 2023c) and its successors (Li et al., 2025b; Alzubi et al., 2025) introduced paradigms where LLMs alternate between reasoning steps and tool use, guiding models to break problems down and issue relevant search queries mid-process. This enables iterative refinement of reasoning with retrieved evidence, improving factuality and coherence. Extensions such as Search-o1 (Li et al., 2025b) and Open Deep Search (ODS) (Alzubi et al., 2025) prompt LLMs to actively consult web resources and integrate results into ongoing thought chains. In parallel, methods like Self-Ask (Press et al., 2023) and IRCoT (Trivedi et al., 2023) embed search directly within step-by-step reasoning, generating sub-questions and retrieving partial answers in a recursive loop. These prompting approaches offer flexible templates to scaffold retrieval-enhanced reasoning. However, they rely on fixed prompting logic and do not provide incentives for exploring better search or reasoning paths, limiting their scalability for open-ended or high-stakes tasks.

Supervised Fine-Tuning: Hard-Coding Search Patterns. Supervised fine-tuning (SFT) takes a more structured approach by directly training LLMs on datasets that combine reasoning and retrieval. Toolformer (Schick et al., 2023) and INTERS (Zhu et al., 2024) illustrate how models can be trained to learn when and how to query external tools, assess retrieved information, and integrate it logically into final outputs. SFT data typically comes from two sources: synthetic data generation (e.g., Toolformer (Schick et al., 2023), RAG-Studio (Mao et al., 2024)) or instructional reformulation of existing datasets (e.g., INTERS (Zhu et al., 2024), InstructRetro (Wang et al., 2024a)). These enable LLMs to follow structured retrieval-reasoning sequences. However, such methods primarily encode static behaviors learned from data, not dynamic, adaptive behaviors optimized for diverse environments. While prompting and SFT offer controlled environments for building retrieval-aware reasoning, they impose fixed search patterns and predefined goals. They do not equip agents with the ability to explore the open-ended, uncertain nature of real-world search tasks.

Reinforcement Learning: Optimizing Reasoning-Driven Search in the Wild. Reinforcement learning (RL) fundamentally changes the search paradigm by letting agents learn through trial and error in interactive environments. Instead of being told how to search, RL-trained agents are incentivized (through feedback or reward functions) to discover, refine, and adapt their reasoning and search strategies for specific goals. Early systems like WebGPT (Nakano et al., 2021) and RAG-RL (Huang et al., 2025a) demonstrated how reward signals (based on human feedback or factual correctness) can guide multi-step retrieval policies that improve response accuracy and trustworthiness. More modular designs like M-RAG (Wang et al., 2024d) separate reasoning and retrieval into specialized agents, each trained to collaborate via shared RL objectives. Recent RL-based systems such as Search-R1 (Jin et al., 2025), R1-Searcher (Song et al., 2025), DeepResearcher (Zheng et al., 2025a), ZeroSearch (Sun et al., 2025a), and WebAgent-R1 (Wei et al., 2025b) operate in various search environments from static local corpora and open search APIs to real-world web interfaces. These agents learn to decompose complex tasks, plan query sequences, verify evidence, and adjust their strategies based on environment feedback. Such behaviors are difficult to teach through SFT or prompts alone. Importantly, ReSearch (Chen et al., 2025b) and ReARTeR (Sun et al., 2025b) go a step further by optimizing not just factual correctness, but also alignment with transparent, interpretable reasoning. ReARTeR introduces a dual-model approach that incentivizes both outcome quality and step-wise explainability, offering a more human-aligned path to trustworthy automation.

#### 3.2 Benchmarks and Open-Source Implementations:

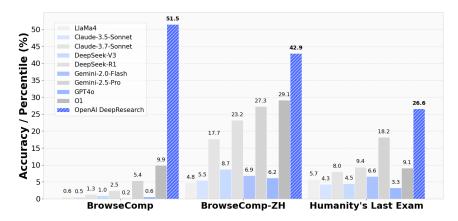
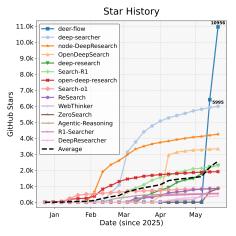


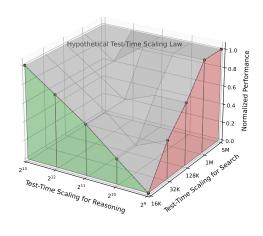
Figure 2: Benchmarks of 5 standard LLMs, 4 reasoning LLMs, and 1 agentic deep research model (OpenAI Deep Research) on BrowseComp, BrowseComp-ZH, and Humanity's Last Exam.

**Deep Research Benchmarks** To rigorously compare the capabilities of standard LLMs, reasoning LLMs, and agentic deep research models in realistic and high-stakes scenarios, we adopt and evaluate three representative benchmarks, including BrowseComp (Wei et al., 2025a), BrowseComp-ZH (Zhou et al., 2025), and Humanity's Last Exam (HLE) (Phan et al., 2025), each targeting distinct dimensions of agentic deep research. BrowseComp assesses an agent's ability to conduct multi-step, open-ended web searches to retrieve non-trivial information, while BrowseComp-ZH extends this challenge to the

Chinese web, introducing additional linguistic complexity. In contrast, HLE focuses on presenting expert-level questions across diverse academic domains that cannot be solved through naive retrieval alone. These tasks require agents to synthesize evidence from obscure or fragmented sources (e.g., identifying policy changes from regional Chinese documents or resolving historical ambiguities) or to reason through abstract academic problems, where more details can be found in Appendix A. As shown in Figure 2, standard LLMs perform poorly across these benchmarks—typically below 10% on BrowseComp datasets and under 20% on HLE. In comparison, the OpenAI Deep Research agent achieves significantly higher scores—51.5% on BrowseComp, 42.9% on BrowseComp-ZH, and 26.6% on HLE—demonstrating the effectiveness of reasoning-integrated search in advancing the frontier of intelligent information-seeking systems.

**Open-Source Implementations** To empirically ground the rising momentum behind Agentic Deep Research, we examine GitHub star trajectories for recent open-source implementations within this paradigm and we provide detailed information in Appendix B. After excluding the two most-starred repositories (to mitigate skew from viral or legacy projects) and the two least-starred (to reduce statistical noise), we observe a clear upward trajectory across nearly all remaining projects since early 2025. Notably, *deep-searcher* and *deer-flow* experienced rapid surges, reaching thousands of stars within weeks. Even smaller-scale efforts, including *DeepResearcher* and *R1-Searcher*, display a consistent upward trend, highlighting the breadth of innovation within the agentic search space. These patterns, along with the average Github star trends, indicate not only a technical transition but also a broader cultural and developmental shift: the open-source community is increasingly converging around reasoning-driven, agentic deep research as a leading framework for information seekin. This empirical momentum reinforces our position statement—that Agentic Deep Research LLM-cored Agentic Deep Research framework will inevitable become the dominant paradigm for future information search.





- (a) GitHub star trend for open-source repositories.
- (b) Test-time scaling law for agentic deep research.

Figure 3: (a) Open-source star trend for agentic deep research. (star counts recorded up to 22 May 2025). (b) Test-time scaling (TTS) law for agentic deep research, where data before performance normalization for reasoning TTS is from S1 on AIME24 (Muennighoff et al., 2025) and for search TTS is from IterDRAG on MuSiQue (Yue et al., 2025). The TTS is measured in inference tokens.

# 4 Test-Time Scaling Law for Deep Research

Building upon the stated position, we introduce the Test-Time Scaling (TTS) law for Agentic Deep Research, an hypothesis predicting the performance improvements achievable through extended computational resources during inference. Figure 3b illustrates this hypothesis, normalized performance improve linearly through scaling of internal reasoning depth and external knowledge exploration. Data supporting this observation comes from two representative evaluations: S1 on the AIME24

dataset (Muennighoff et al., 2025), which tests reasoning-based scaling on advanced multi-step mathematical reasoning problems, and IterDRAG on MuSiQue (Yue et al., 2025), which focuses on search-based scaling via multi-hop retrieval tasks. As in Figure 3b, the diagonal plane connecting empirical data points interpolated in the three-dimensional plot represents our hypothetical TTS for Agentic Deep Research. Tasks requiring deeper internal knowledge utilization (reasoning), such as solving complex math problems and logic puzzles, are better aligned with the green plane, whereas tasks demanding extensive external knowledge exploration (search), like medical QA, will align more closely with the red plane. Here, we illustrate the TTS law and trade-offs along the search and reasoning axes.

#### 4.1 Reasoning — TTS of Internal Knowledge Utilization

Recent studies have shown that LLMs do more than recall memorized facts or patterns. When given extra computational resource to "think", they can also perform deeper reasoning steps. This pattern, known as the test-time scaling law for reasoning, indicates that as a model takes more inference steps, including building longer chains of thought (Chen et al., 2025c), iterative self-refinement (Madaan et al., 2023), or self-consistency decoding (Hao et al., 2023), its accuracy in complex tasks steadily improves. This phenomenon also suggests that the internal knowledge embedded in LLMs is not fully exposed in a single forward pass. Instead, deeper understanding can be progressively uncovered through extended inference. In the context of Agentic Deep Research, this highlights a key shift from producing one-shot answers to engaging in active, multi-step reasoning. Instead of relying solely on external retrieval or prompting tricks, the model's internal knowledge becomes a reusable and expandable resource. This inference-time flexibility is crucial for handling complex, open-ended queries, and positions reasoning as a core axis of scalable capability in LLM-based research agents (Huang et al., 2024).

#### 4.2 Search — TTS of External Knowledge Exploration

In addition to making full use of the internal knowledge of LLMs, exploring abundant external knowledge effectively is another key to achieving TTS in Agentic Deep Research systems. When performing external knowledge search, it is often difficult to obtain all the important information in a single-step retrieval (Shao et al., 2023; Jiang et al., 2024). To overcome this bottleneck, consistent with the agentic RAG insights, existing work mainly explores the scaling potential of the search phase through *iterative* search and *long-context* RAG. Representatively, many works have explored improving the test-time retrieval performance through iterative RAG/search, which introduces a dynamic and multi-step retrieval to knowledge search via task decomposition (Trivedi et al., 2023; Asai et al., 2023; Xiong et al., 2024). They generally show that iterative multi-step retrieval under a proper number of iterations can also enhance RAG's performance. Yue et al. (2025) recently further observed an important experimental phenomenon that under optimal inference parameters, the performance improves nearly linearly with increasing test-time computation. The gradual expansion of knowledge retrieval from split local text chunks towards an increasingly precise retrieval executed within nearly global external knowledge bases would become a more powerful development trend in the test-time search process.

#### 4.3 TTS Trade-offs for Search and Reasoning

Agentic Deep Research systems integrate both search and reasoning, each consuming part of a limited token budget. Under such constraints, a natural trade-off emerges: allocating more tokens to search (e.g., issuing broader or more detailed queries) reduces the capacity available for reasoning (e.g., multi-hop inference or synthesis), and vice versa. This balance is task-dependent. Search-heavy tasks such as multi-hop RAG (Xiong et al., 2024; Shao et al., 2023) or literature surveys prioritize broader content access, while reasoning-heavy tasks like causal analysis or math verification (Snell et al., 2024) require deeper internal processing. Building systems that adaptively allocate token budgets between search and reasoning based on task characteristics is critical for maximizing effectiveness and efficiency in Agentic Deep Research. We anticipate the emergence of a test-time scaling law that governs the optimal balance between search and reasoning under different task conditions. Furthermore, training models that can dynamically allocate and manage budget across these two components is a defining capability of next-generation deep research systems.

#### 5 Alternative View and Discussions

**Retaining Human Primacy in Search** In contrast to the position advanced in this paper that the future of information seeking paradigm is LLM-driven Agentic Deep Research. An alternative viewpoint contends that search should remain fundamentally a human-led activity, with artificial intelligence systems serving primarily as assistive, not autonomous, tools. This counter-position emphasizes that human with primary involvement is indispensable for ensuring trust, interpretability, and epistemic responsibility in open-ended inquiry tasks (Mehrotra et al., 2024). First, despite the recent progress in agentic reasoning capabilities, autonomous systems still lack robust models of user intent, contextual nuance, and domain-specific ethics. These elements are often essential in complex or high-stakes search scenarios such as scientific research, legal interpretation, or public policy analysis. Advocates of human-led search argue that delegating the full pipeline (from information retrieval to reasoning and synthesis) to LLM agents risks introducing misaligned conclusions, opaque decision paths, and reduced user oversight. In addition, from a trust and accountability perspective, human-directed systems afford greater transparency and traceability. While autonomous agents can produce fluent and plausible outputs, they also introduce increased risk of hallucinations, spurious correlations, or unjustified reasoning steps. Maintaining human control over search allows users to apply critical judgment, verify information provenance, and assume responsibility for downstream decisions, a particularly salient concern in regulated or high-risk domains (Zou et al., 2025b,c).

# **6** Open Problems and Future Opportunities

Human-in-Loop and Trustworthy This suggests that progress in AI search systems should prioritize augmenting human capabilities rather than replacing them. This includes building interfaces that support iterative refinement, expose intermediate reasoning steps, and enable meaningful user feedback. In this framing, AI functions less as an autonomous researcher and more as a powerful assistant embedded within a human-centered workflow (Shneiderman, 2022). To build trustworthy Deep Research systems, human interactions play an important role. Several important research questions need to be solved. (1) Search Content Access Control. Implementing fine-grained access control mechanisms ensures that users can only access information appropriate to their roles and permissions. This is particularly important in domains where role-based access to information is essential for privacy, regulatory compliance, or competitive confidentiality. (2) Human Verification and Feedback Mechanisms. Incorporating human oversight at critical stages of the AI search process can significantly improve the accuracy and reliability of the system (Zou et al., 2025b,c). Designing systems that facilitate user feedback enables continuous learning and adaptation, aligning AI outputs more closely with user expectations (Zhong et al., 2024; Zou et al., 2025c) and user-specific requirements (Zhang et al., 2025b).

**In-Domain Expert-Level Deep Research** Deep Research is emerging as the new internet traffic entrance and current Deep Research systems focus on general-purpose domains. However, in highly specialized fields such as medicine, law, and biology, in-domain expert-level deep research is essential to ensure accuracy, relevance, and usability. Domain-specific research poses unique challenges that general-purpose agents cannot meet. We highlight three key research directions: (1) Domain-Specific Database Construction. In many fields, data is scattered across fragmented databases with inconsistent coverage and interfaces—e.g., in bioinformatics (Benson et al., 2012; UniProt Consortium, 2018; Dyer et al., 2025) or medicine (Knox et al., 2024; Landrum et al., 2018). This fragmentation hampers retrieval and reasoning. Future systems must build unified, structured, and queryable domain-specific databases to enable effective deep research. (2) Domain-Grounded Reasoning. Reasoning paradigms vary by field: legal reasoning relies on precedent, medical reasoning on diagnostic codes, scientific reasoning on hypothesis testing. Agentic systems must align with these paradigms, adapting their planning and inference mechanisms to domain-specific logic and workflows.

**Structure-Organized Deep Research Systems** Structured (graph) data, composed of nodes (representing entities) and edges (representing relationships), offers an intuitive and systematic way to represent complex relationships and knowledge associations (Hamilton et al., 2017; Veličković et al., 2018). This structured organization can significantly enhance the deep research process in the following ways: (1) Iterative Data Organization: There are many intermediate searching and reasoning contents during agentic retrieval and reasoning. Structuring these iterative contents helps

agents maintain coherence and relevance in the long context (Li et al., 2024). As structured data clarifies knowledge relationships, agents can follow these links effectively when generating answers. This allows them to find relevant content more clearly and avoid contradictions or illogical situations. (2) Multi-Agent Deep Research: Effective task allocation and coordination are essential in multi-agent collaboration (Luo et al., 2025a). Graph structure helps agents understand task requirements based on their roles and relationships (Zhuge et al., 2024; Zhang et al., 2024b). Further, in multi-agent collaboration, timely and accurate information exchange is vital. Graph data serves as an effective information carrier, allowing agents to structure complex information. Learning (message passing) from this structured data enhances efficient information sharing among agents based on their relationships.

From Textual Space to Multi-Modality For Agentic Deep Research systems to truly emulate human research capabilities, they must transcend textual limitations and integrate diverse information modalities including images, audio-visual content, and structured data. Different modalities inherently encode distinct knowledge types: text conveys abstract concepts and logical relationships, images provide visual instances and spatial information, while videos capture temporal dynamics and sequential processes. This evolution requires a qualitative cognitive leap in knowledge integration rather than merely expanding input channels. Critical research directions include: (1) Cross-modal Semantic Alignment: deep cross-modal semantic alignment within unified representational spaces that support context-aware reasoning across modalities (Li et al., 2025a); (2) Information Fusion and Conflict Resolution: robust information fusion with sophisticated conflict resolution mechanisms when modalities present inconsistent information (Bi et al., 2025); and (3) Multi-modal Knowledge Acquisition: efficient multi-modal knowledge retrieval and comprehension from heterogeneous, large-scale data repositories (Abootorabi et al., 2025).

Efficient Test-Time Scaling As Agentic Deep Research systems advance, operational efficiency and cost management become critical scaling determinants. Optimization must target both reasoning and search: (1) Reasoning Efficiency, balancing computational depth against resource utilization through techniques like capability transfer to smaller models or latent reasoning approaches (Sui et al., 2025). Such efficiency improvements potentially extend beyond mere compression of reasoning chains to manifest as higher-order intelligence through resource self-management (Li et al., 2025d). (2) Search Efficiency: Optimizing search beyond naive retrieval requires addressing scalable retrieval from massive heterogeneous sources, efficient long-context processing (Luo et al., 2025b), and iterative search with intelligent query refinement and adaptive stopping criteria (Singh et al., 2025). Future systems must implement budget-aware strategies that dynamically adjust search workflows.

# 7 Conclusion

This paper has articulated a compelling trajectory from traditional web search paradigms towards the inevitable ascendancy of Agentic Deep Research. By systematically addressing the limitations of prior search engine systems and emphasizing the transformative potential of iterative reasoning and search enabled through advanced reinforcement learning frameworks, we demonstrate that agentic systems significantly outperform traditional models across complex benchmarks. The empirical trends observed in both academic evaluations and open-source implementations reinforce this shift, indicating broad recognition and adoption within different communities. Nevertheless, recognizing legitimate concerns regarding human oversight and transparency, future developments must incorporate hybrid frameworks that optimize both autonomous agentic capabilities and human-in-the-loop interactions. In proposing multiple open challenges and opportunities, we foresee Agentic Deep Research as not only the dominant paradigm but also a profoundly human-centered LLM-driven advancement in knowledge acquisition and synthesis.

# References

Abootorabi, M. M., Zobeiri, A., Dehghani, M., Mohammadkhani, M., Mohammadi, B., Ghahroodi, O., Baghshah, M. S., and Asgari, E. (2025). Ask in any modality: A comprehensive survey on multimodal retrieval-augmented generation. *arXiv* preprint arXiv:2502.08826.

Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., et al. (2023). Gpt-4 technical report. arXiv preprint arXiv:2303.08774.

- Alzubi, S., Brooks, C., Chiniya, P., Contente, E., von Gerlach, C., Irwin, L., Jiang, Y., Kaz, A., Nguyen, W., Oh, S., et al. (2025). Open deep search: Democratizing search with open-source reasoning agents. *arXiv preprint arXiv:2503.20201*.
- Amendola, M., Passarella, A., and Perego, R. (2023). Social search: Retrieving information in online social platforms—a survey. *Online Social Networks and Media*, 36:100254.
- Anthropic (2023). Claude. https://www.anthropic.com. Accessed: 2025-06-03.
- Asai, A., Wu, Z., Wang, Y., Sil, A., and Hajishirzi, H. (2023). Self-rag: Learning to retrieve, generate, and critique through self-reflection. In *The Twelfth International Conference on Learning Representations*.
- Baek, J., Jauhar, S. K., Cucerzan, S., and Hwang, S. J. (2024). Researchagent: Iterative research idea generation over scientific literature with large language models. *arXiv preprint arXiv:2404.07738*.
- Bai, Y., Jones, A., Ndousse, K., Askell, A., Chen, A., DasSarma, N., Drain, D., Fort, S., Ganguli, D., Henighan, T., et al. (2022). Training a helpful and harmless assistant with reinforcement learning from human feedback. arXiv preprint arXiv:2204.05862.
- Benson, D. A., Cavanaugh, M., Clark, K., Karsch-Mizrachi, I., Lipman, D. J., Ostell, J., and Sayers, E. W. (2012). Genbank. *Nucleic acids research*, 41(D1):D36–D42.
- Bi, J., Liang, S., Zhou, X., Liu, P., Guo, J., Tang, Y., Song, L., Huang, C., Sun, G., He, J., et al. (2025). Why reasoning matters? a survey of advancements in multimodal reasoning (v1). *arXiv preprint arXiv:2504.03151*.
- Brin, S. and Page, L. (1998). The anatomy of a large-scale hypertextual web search engine. *Computer networks and ISDN systems*, 30(1-7):107–117.
- Broder, A. (2002). A taxonomy of web search. In *ACM Sigir forum*, volume 36, pages 3–10. ACM New York, NY, USA.
- Callison-Burch, C., Tomar, G. S., Martin, L. J., Ippolito, D., Bailis, S., and Reitter, D. (2022). Dungeons and dragons as a dialog challenge for artificial intelligence. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9379–9393.
- Chen, C. and Shu, K. (2023). Can Ilm-generated misinformation be detected? In *NeurIPS 2023 Workshop on Regulatable ML*.
- Chen, D. and Yih, W.-t. (2020). Open-domain question answering. In *Proceedings of the 58th annual meeting of the association for computational linguistics: tutorial abstracts*, pages 34–37.
- Chen, M., Li, T., Sun, H., Zhou, Y., Zhu, C., Wang, H., Pan, J. Z., Zhang, W., Chen, H., Yang, F., et al. (2025a). Research: Learning to reason with search for llms via reinforcement learning. *arXiv* preprint arXiv:2503.19470.
- Chen, M., Li, T., Sun, H., Zhou, Y., Zhu, C., Yang, F., Zhou, Z., Chen, W., Wang, H., Pan, J. Z., et al. (2025b). Learning to reason with search for llms via reinforcement learning. *arXiv* preprint *arXiv*:2503.19470.
- Chen, Q., Qin, L., Liu, J., Peng, D., Guan, J., Wang, P., Hu, M., Zhou, Y., Gao, T., and Che, W. (2025c). Towards reasoning era: A survey of long chain-of-thought for reasoning large language models. *arXiv preprint arXiv:2503.09567*.
- Cheng, M., Luo, Y., Ouyang, J., Liu, Q., Liu, H., Li, L., Yu, S., Zhang, B., Cao, J., Ma, J., et al. (2025). A survey on knowledge-oriented retrieval-augmented generation. *arXiv preprint arXiv:2503.10677*.
- Dyer, S. C., Austine-Orimoloye, O., Azov, A. G., Barba, M., Barnes, I., Barrera-Enriquez, V. P., Becker, A., Bennett, R., Beracochea, M., Berry, A., et al. (2025). Ensembl 2025. *Nucleic Acids Research*, 53(D1):D948–D957.
- Fuhr, N. (1992). Probabilistic models in information retrieval. *The computer journal*, 35(3):243–255.

- Ghosh, S., Evuru, C. K. R., Kumar, S., S, R., Aneja, D., Jin, Z., Duraiswami, R., and Manocha, D. (2024). A closer look at the limitations of instruction tuning. In *Proceedings of the 41st International Conference on Machine Learning*, pages 15559–15589.
- Gu, Z., Zou, H. P., Chen, Y., Liu, A., Zhang, W., and Yu, P. S. (2025). Scaling laws for many-shot in-context learning with self-generated annotations. *arXiv preprint arXiv:2503.03062*.
- Guo, D., Yang, D., Zhang, H., Song, J., Zhang, R., Xu, R., Zhu, Q., Ma, S., Wang, P., Bi, X., et al. (2025). Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv* preprint arXiv:2501.12948.
- Hamilton, W. L., Ying, R., and Leskovec, J. (2017). Inductive representation learning on large graphs. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, pages 1025–1035.
- Hao, S., Gu, Y., Ma, H., Hong, J., Wang, Z., Wang, D., and Hu, Z. (2023). Reasoning with language model is planning with world model. In *Proceedings of the 2023 Conference on Empirical Methods* in *Natural Language Processing*. Association for Computational Linguistics.
- Hendriksen, G., Dinzinger, M., Farzana, S. M., Fathima, N. A., Fröbe, M., Schmidt, S., Zerhoudi, S., Granitzer, M., Hagen, M., Hiemstra, D., et al. (2024). The open web index: Crawling and indexing the web for public use. In *European Conference on Information Retrieval*, pages 130–143. Springer.
- Huang, J., Madala, S., Sidhu, R., Niu, C., Hockenmaier, J., and Zhang, T. (2025a). Rag-rl: Advancing retrieval-augmented generation via rl and curriculum learning. *arXiv preprint arXiv:2503.12759*.
- Huang, X., Liu, W., Chen, X., Wang, X., Wang, H., Lian, D., Wang, Y., Tang, R., and Chen, E. (2024). Understanding the planning of llm agents: A survey. *arXiv preprint arXiv:2402.02716*.
- Huang, Z., Yuan, X., Ju, Y., Zhao, J., and Liu, K. (2025b). Reinforced internal-external knowledge synergistic reasoning for efficient adaptive search agent. *arXiv preprint arXiv:2505.07596*.
- Iyer, S., Lin, X. V., Pasunuru, R., Mihaylov, T., Simig, D., Yu, P., Shuster, K., Wang, T., Liu, Q., Koura, P. S., et al. (2022). Opt-iml: Scaling language model instruction meta learning through the lens of generalization. *arXiv* preprint arXiv:2212.12017.
- Jaech, A., Kalai, A., Lerer, A., Richardson, A., El-Kishky, A., Low, A., Helyar, A., Madry, A., Beutel, A., Carney, A., et al. (2024). Openai o1 system card. arXiv preprint arXiv:2412.16720.
- Jiang, Z., Sun, M., Liang, L., and Zhang, Z. (2024). Retrieve, summarize, plan: Advancing multi-hop question answering with an iterative approach. *arXiv preprint arXiv:2407.13101*.
- Jiang, Z., Xu, F. F., Gao, L., Sun, Z., Liu, Q., Dwivedi-Yu, J., Yang, Y., Callan, J., and Neubig, G. (2023). Active retrieval augmented generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 7969–7992.
- Jin, B., Zeng, H., Yue, Z., Wang, D., Zamani, H., and Han, J. (2025). Search-r1: Training llms to reason and leverage search engines with reinforcement learning. *arXiv* preprint arXiv:2503.09516.
- Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., et al. (2023). Chatgpt for good? on opportunities and challenges of large language models for education. *Learning and individual differences*, 103:102274.
- Khder, M. A. (2021). Web scraping or web crawling: State of art, techniques, approaches and application. *International Journal of Advances in Soft Computing & Its Applications*, 13(3).
- Knox, C., Wilson, M., Klinger, C. M., Franklin, M., Oler, E., Wilson, A., Pon, A., Cox, J., Chin, N. E., Strawbridge, S. A., et al. (2024). Drugbank 6.0: the drugbank knowledgebase for 2024. Nucleic acids research, 52(D1):D1265–D1275.
- Landrum, M. J., Lee, J. M., Benson, M., Brown, G. R., Chao, C., Chitipiralla, S., Gu, B., Hart, J., Hoffman, D., Jang, W., et al. (2018). Clinvar: improving access to variant interpretations and supporting evidence. *Nucleic acids research*, 46(D1):D1062–D1067.

- Leake, D. B. and Scherle, R. (2001). Towards context-based search engine selection. In *Proceedings* of the 6th international conference on Intelligent user interfaces, pages 109–112.
- Li, M., Su, N., Qu, F., Zhong, Z., Chen, Z., Tu, Z., and Li, X. (2025a). Vista: Enhancing vision-text alignment in mllms via cross-modal mutual information maximization. *arXiv* preprint *arXiv*:2505.10917.
- Li, S., He, Y., Guo, H., Bu, X., Bai, G., Liu, J., Liu, J., Qu, X., Li, Y., Ouyang, W., et al. (2024). Graphreader: Building graph-based agent to enhance long-context abilities of large language models. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 12758–12786.
- Li, X., Dong, G., Jin, J., Zhang, Y., Zhou, Y., Zhu, Y., Zhang, P., and Dou, Z. (2025b). Search-o1: Agentic search-enhanced large reasoning models. *arXiv preprint arXiv:2501.05366*.
- Li, X., Jin, J., Dong, G., Qian, H., Zhu, Y., Wu, Y., Wen, J.-R., and Dou, Z. (2025c). Webthinker: Empowering large reasoning models with deep research capability. *arXiv preprint arXiv:2504.21776*.
- Li, X. L. and Liang, P. (2021). Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597.
- Li, Z., Dong, Q., Ma, J., Zhang, D., and Sui, Z. (2025d). Selfbudgeter: Adaptive token allocation for efficient llm reasoning. *arXiv* preprint arXiv:2505.11274.
- Linden, G., Meek, C., Chickering, M., and Meek, C. (2009). The pollution effect: Optimizing keyword auctions by favoring relevant advertising. In *Fifth workshop on Ad Auctions*.
- Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., Wu, Z., Zhao, L., Zhu, D., Li, X., Qiang, N., Shen, D., Liu, T., and Ge, B. (2023). Summary of chatgpt-related research and perspective towards the future of large language models. *Meta-Radiology*, 1(2):100017.
- Lu, C., Lu, C., Lange, R. T., Foerster, J., Clune, J., and Ha, D. (2024). The ai scientist: Towards fully automated open-ended scientific discovery. *arXiv preprint arXiv:2408.06292*.
- Luo, J., Zhang, W., Yuan, Y., Zhao, Y., Yang, J., Gu, Y., Wu, B., Chen, B., Qiao, Z., Long, Q., et al. (2025a). Large language model agent: A survey on methodology, applications and challenges. *arXiv* preprint arXiv:2503.21460.
- Luo, K., Liu, Z., Zhang, P., Qian, H., Zhao, J., and Liu, K. (2025b). Does rag really perform bad for long-context processing? *arXiv preprint arXiv:2502.11444*.
- Ma, X., Gong, Y., He, P., Zhao, H., and Duan, N. (2023). Query rewriting in retrieval-augmented large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 5303–5315.
- Madaan, A., Tandon, N., Gupta, P., Hallinan, S., Gao, L., Wiegreffe, S., Alon, U., Dziri, N., Prabhumoye, S., Yang, Y., et al. (2023). Self-refine: Iterative refinement with self-feedback. *Advances in Neural Information Processing Systems*, 36:46534–46594.
- Mao, K., Liu, Z., Qian, H., Mo, F., Deng, C., and Dou, Z. (2024). Rag-studio: Towards in-domain adaptation of retrieval augmented generation through self-alignment. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 725–735.
- Mehrotra, S., Degachi, C., Vereschak, O., Jonker, C. M., and Tielman, M. L. (2024). A systematic review on fostering appropriate trust in human-ai interaction: Trends, opportunities and challenges. *ACM Journal on Responsible Computing*, 1(4):1–45.
- Mo, F., Mao, K., Zhao, Z., Qian, H., Chen, H., Cheng, Y., Li, X., Zhu, Y., Dou, Z., and Nie, J.-Y. (2024). A survey of conversational search.

- Muennighoff, N., Yang, Z., Shi, W., Li, X. L., Fei-Fei, L., Hajishirzi, H., Zettlemoyer, L., Liang, P., Candès, E., and Hashimoto, T. (2025). s1: Simple test-time scaling. arXiv preprint arXiv:2501.19393.
- Nakano, R., Hilton, J., Balaji, S., Wu, J., Ouyang, L., Kim, C., Hesse, C., Jain, S., Kosaraju, V., Saunders, W., et al. (2021). Webgpt: Browser-assisted question-answering with human feedback. arXiv preprint arXiv:2112.09332.
- Noruzi, A. (2005). Google scholar: The new generation of citation indexes.
- Page, L., Brin, S., Motwani, R., and Winograd, T. (1999). The pagerank citation ranking: Bringing order to the web. Technical report, Stanford infolab.
- Peng, B., Galley, M., He, P., Cheng, H., Xie, Y., Hu, Y., Huang, Q., Liden, L., Yu, Z., Chen, W., et al. (2023). Check your facts and try again: Improving large language models with external knowledge and automated feedback. *arXiv* preprint arXiv:2302.12813.
- Phan, L., Gatti, A., Han, Z., Li, N., Hu, J., Zhang, H., Zhang, C. B. C., Shaaban, M., Ling, J., Shi, S., et al. (2025). Humanity's last exam. *arXiv preprint arXiv:2501.14249*.
- Prabhune, S. and Berndt, D. J. (2024). Deploying large language models with retrieval augmented generation. *arXiv* preprint arXiv:2411.11895.
- Press, O., Zhang, M., Min, S., Schmidt, L., Smith, N. A., and Lewis, M. (2023). Measuring and narrowing the compositionality gap in language models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5687–5711.
- Robertson, S., Zaragoza, H., et al. (2009). The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends*® *in Information Retrieval*, 3(4):333–389.
- Sami, A. M., Rasheed, Z., Kemell, K.-K., Waseem, M., Kilamo, T., Saari, M., Duc, A. N., Systä, K., and Abrahamsson, P. (2024). System for systematic literature review using multiple ai agents: Concept and an empirical evaluation.
- Schick, T., Dwivedi-Yu, J., Dessì, R., Raileanu, R., Lomeli, M., Hambro, E., Zettlemoyer, L., Cancedda, N., and Scialom, T. (2023). Toolformer: Language models can teach themselves to use tools. *Advances in Neural Information Processing Systems*, 36:68539–68551.
- Schmidgall, S., Su, Y., Wang, Z., Sun, X., Wu, J., Yu, X., Liu, J., Liu, Z., and Barsoum, E. (2025). Agent laboratory: Using llm agents as research assistants. *arXiv preprint arXiv:2501.04227*.
- Shao, Z., Gong, Y., Shen, Y., Huang, M., Duan, N., and Chen, W. (2023). Enhancing retrieval-augmented large language models with iterative retrieval-generation synergy. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 9248–9274.
- Shneiderman, B. (2022). *Human-centered AI*. Oxford University Press.
- Singh, A., Ehtesham, A., Kumar, S., and Khoei, T. T. (2025). Agentic retrieval-augmented generation: A survey on agentic rag. *arXiv preprint arXiv:2501.09136*.
- Snell, C., Lee, J., Xu, K., and Kumar, A. (2024). Scaling llm test-time compute optimally can be more effective than scaling model parameters. *arXiv preprint arXiv:2408.03314*.
- Song, H., Jiang, J., Min, Y., Chen, J., Chen, Z., Zhao, W. X., Fang, L., and Wen, J.-R. (2025). R1-searcher: Incentivizing the search capability in llms via reinforcement learning. *arXiv* preprint *arXiv*:2503.05592.
- Sui, Y., Chuang, Y.-N., Wang, G., Zhang, J., Zhang, T., Yuan, J., Liu, H., Wen, A., Zhong, S., Chen, H., et al. (2025). Stop overthinking: A survey on efficient reasoning for large language models. *arXiv preprint arXiv:2503.16419*.
- Sun, H., Qiao, Z., Guo, J., Fan, X., Hou, Y., Jiang, Y., Xie, P., Huang, F., and Zhang, Y. (2025a). Zerosearch: Incentivize the search capability of Ilms without searching. *arXiv* preprint *arXiv*:2505.04588.

- Sun, Z., Wang, Q., Yu, W., Zang, X., Zheng, K., Xu, J., Zhang, X., Yang, S., and Li, H. (2025b). Rearter: Retrieval-augmented reasoning with trustworthy process rewarding. *arXiv* preprint arXiv:2501.07861.
- Tam, D., Mascarenhas, A., Zhang, S., Kwan, S., Bansal, M., and Raffel, C. (2023). Evaluating the factual consistency of large language models through news summarization. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 5220–5255.
- Thirunavukarasu, A. J., Ting, D. S. J., Elangovan, K., Gutierrez, L., Tan, T. F., and Ting, D. S. W. (2023). Large language models in medicine. *Nature medicine*, 29(8):1930–1940.
- Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., Bashlykov, N., Batra, S., Bhargava, P., Bhosale, S., et al. (2023). Llama 2: Open foundation and fine-tuned chat models. *arXiv* preprint arXiv:2307.09288.
- Trivedi, H., Balasubramanian, N., Khot, T., and Sabharwal, A. (2023). Interleaving retrieval with chain-of-thought reasoning for knowledge-intensive multi-step questions. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 10014–10037.
- UniProt Consortium, T. (2018). Uniprot: the universal protein knowledgebase. *Nucleic acids research*, 46(5):2699–2699.
- Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., and Bengio, Y. (2018). Graph attention networks. In *International Conference on Learning Representations*.
- Wang, B., Min, S., Deng, X., Shen, J., Wu, Y., Zettlemoyer, L., and Sun, H. (2023a). Towards understanding chain-of-thought prompting: An empirical study of what matters. In *The 61st Annual Meeting Of The Association For Computational Linguistics*.
- Wang, B., Ping, W., Mcafee, L., Xu, P., Li, B., Shoeybi, M., and Catanzaro, B. (2024a). Instructretro: Instruction tuning post retrieval-augmented pretraining. In *International Conference on Machine Learning*, pages 51255–51272. PMLR.
- Wang, H., Fu, T., Du, Y., Gao, W., Huang, K., Liu, Z., Chandak, P., Liu, S., Van Katwyk, P., Deac, A., et al. (2023b). Scientific discovery in the age of artificial intelligence. *Nature*, 620(7972):47–60.
- Wang, J., Lu, T., Li, L., Huang, D., et al. (2024b). Enhancing personalized search with ai: a hybrid approach integrating deep learning and cloud computing. *Journal of Advanced Computing Systems*, 4(10):1–13.
- Wang, X., Feng, M., Qiu, J., Gu, J., and Zhao, J. (2024c). From news to forecast: Integrating event analysis in llm-based time series forecasting with reflection. *Advances in Neural Information Processing Systems*, 37:58118–58153.
- Wang, Z., Teo, S. X., Ouyang, J., Xu, Y., and Shi, W. (2024d). M-rag: Reinforcing large language model performance through retrieval-augmented generation with multiple partitions. arXiv preprint arXiv:2405.16420.
- Wei, J., Sun, Z., Papay, S., McKinney, S., Han, J., Fulford, I., Chung, H. W., Passos, A. T., Fedus, W., and Glaese, A. (2025a). Browsecomp: A simple yet challenging benchmark for browsing agents. *arXiv preprint arXiv:2504.12516*.
- Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E., Le, Q. V., Zhou, D., et al. (2022). Chain-of-thought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35:24824–24837.
- Wei, Z., Yao, W., Liu, Y., Zhang, W., Lu, Q., Qiu, L., Yu, C., Xu, P., Zhang, C., Yin, B., et al. (2025b). Webagent-r1: Training web agents via end-to-end multi-turn reinforcement learning. arXiv preprint arXiv:2505.16421.
- Wu, J., Zhu, J., and Liu, Y. (2025). Agentic reasoning: Reasoning llms with tools for the deep research. *arXiv preprint arXiv:2502.04644*.

- Xiong, G., Jin, Q., Wang, X., Zhang, M., Lu, Z., and Zhang, A. (2024). Improving retrieval-augmented generation in medicine with iterative follow-up questions. In *Biocomputing 2025: Proceedings of the Pacific Symposium*, pages 199–214. World Scientific.
- Yang, W., Zhang, W., Liu, Y., Han, Y., Wang, Y., Lee, J., and Yu, P. S. (2025). Cold-start recommendation with knowledge-guided retrieval-augmented generation. *arXiv preprint arXiv:2505.20773*.
- Yang, Y., Yih, W.-t., and Meek, C. (2015). Wikiqa: A challenge dataset for open-domain question answering. In *Proceedings of the 2015 conference on empirical methods in natural language processing*, pages 2013–2018.
- Yao, J.-Y., Ning, K.-P., Liu, Z.-H., Ning, M.-N., Liu, Y.-Y., and Yuan, L. (2023a). Llm lies: Hallucinations are not bugs, but features as adversarial examples. *arXiv* preprint arXiv:2310.01469.
- Yao, S., Yu, D., Zhao, J., Shafran, I., Griffiths, T., Cao, Y., and Narasimhan, K. (2023b). Tree of thoughts: Deliberate problem solving with large language models. *Advances in neural information* processing systems, 36:11809–11822.
- Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., and Cao, Y. (2023c). React: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations* (ICLR).
- Yue, Z., Zhuang, H., Bai, A., Hui, K., Jagerman, R., Zeng, H., Qin, Z., Wang, D., Wang, X., and Bendersky, M. (2025). Inference scaling for long-context retrieval augmented generation. In *The Thirteenth International Conference on Learning Representations*.
- Zeng, A., Liu, X., Du, Z., Wang, Z., Lai, H., Ding, M., Yang, Z., Xu, Y., Zheng, W., Xia, X., et al. (2022). Glm-130b: An open bilingual pre-trained model. *arXiv preprint arXiv:2210.02414*.
- Zhang, E., Wang, X., Gong, P., Lin, Y., and Mao, J. (2024a). Usimagent: Large language models for simulating search users. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2687–2692.
- Zhang, G., Yue, Y., Sun, X., Wan, G., Yu, M., Fang, J., Wang, K., Chen, T., and Cheng, D. (2024b). G-designer: Architecting multi-agent communication topologies via graph neural networks. *arXiv* preprint arXiv:2410.11782.
- Zhang, N., Zhang, C., Tan, Z., Yang, X., Deng, W., and Wang, W. (2025a). Credible plan-driven rag method for multi-hop question answering. *arXiv preprint arXiv:2504.16787*.
- Zhang, S., Roller, S., Goyal, N., Artetxe, M., Chen, M., Chen, S., Dewan, C., Diab, M., Li, X., Lin, X. V., et al. (2022). Opt: Open pre-trained transformer language models. *arXiv* preprint *arXiv*:2205.01068.
- Zhang, W., Zhang, X., Zhang, C., Yang, L., Shang, J., Wei, Z., Zou, H. P., Huang, Z., Wang, Z., Gao, Y., et al. (2025b). Personaagent: When large language model agents meet personalization at test time. *arXiv preprint arXiv:2506.06254*.
- Zhao, Y., Zhang, Q., Luo, X., Zhang, W., Xiao, Z., Ju, W., Yu, P. S., and Zhang, M. (2025). Dynamic text bundling supervision for zero-shot inference on text-attributed graphs. *arXiv* preprint *arXiv*:2505.17599.
- Zheng, Y., Fu, D., Hu, X., Cai, X., Ye, L., Lu, P., and Liu, P. (2025a). Deepresearcher: Scaling deep research via reinforcement learning in real-world environments. *arXiv preprint arXiv:2504.03160*.
- Zheng, Z., Ni, X., and Hong, P. (2025b). Multiple abstraction level retrieve augment generation. *arXiv* preprint arXiv:2501.16952.
- Zhong, W., Guo, L., Gao, Q., Ye, H., and Wang, Y. (2024). Memorybank: Enhancing large language models with long-term memory. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 19724–19731.
- Zhou, P., Leon, B., Ying, X., Zhang, C., Shao, Y., Ye, Q., Chong, D., Jin, Z., Xie, C., Cao, M., et al. (2025). Browsecomp-zh: Benchmarking web browsing ability of large language models in chinese. *arXiv* preprint arXiv:2504.19314.

- Zhou, Y., Muresanu, A. I., Han, Z., Paster, K., Pitis, S., Chan, H., and Ba, J. (2022). Large language models are human-level prompt engineers. In *The Eleventh International Conference on Learning Representations*.
- Zhu, Y., Zhang, P., Zhang, C., Chen, Y., Xie, B., Liu, Z., Wen, J.-R., and Dou, Z. (2024). Inters: Unlocking the power of large language models in search with instruction tuning. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2782–2809.
- Zhuge, M., Wang, W., Kirsch, L., Faccio, F., Khizbullin, D., and Schmidhuber, J. (2024). Gptswarm: Language agents as optimizable graphs. In *International Conference on Machine Learning*, pages 62743–62767. PMLR.
- Zou, H. P., Gu, Z., Zhou, Y., Chen, Y., Zhang, W., Fang, L., Wang, Y., Li, Y., Liu, K., and Yu, P. S. (2025a). Testnuc: Enhancing test-time computing approaches and scaling through neighboring unlabeled data consistency. *arXiv* preprint arXiv:2502.19163.
- Zou, H. P., Huang, W.-C., Wu, Y., Chen, Y., Miao, C., Nguyen, H., Zhou, Y., Zhang, W., Fang, L., He, L., et al. (2025b). A survey on large language model based human-agent systems. *arXiv preprint arXiv:2505.00753*.
- Zou, H. P., Huang, W.-C., Wu, Y., Miao, C., Li, D., Liu, A., Zhou, Y., Chen, Y., Zhang, W., Li, Y., et al. (2025c). A call for collaborative intelligence: Why human-agent systems should precede ai autonomy. *arXiv preprint arXiv:2506.09420*.

# A Deep ReSearch Benchmarks

**BrowseComp** (Wei et al., 2025a) is a benchmark introduced by OpenAI to evaluate the capabilities of AI agents in conducting complex web searches. Comprising 1,266 challenging questions, it assesses an agent's ability to persistently navigate the internet to locate hard-to-find, entangled information. Unlike traditional benchmarks that focus on retrieving easily accessible facts, BrowseComp emphasizes tasks where answers are deliberately obscured, requiring agents to demonstrate advanced reasoning, strategic search planning, and adaptability. The benchmark's design ensures that while answers are difficult to discover, they are straightforward to verify, facilitating reliable evaluation of agent performance. BrowseComp serves as a critical tool for advancing research in developing AI systems capable of sophisticated information retrieval and reasoning across the web.

BrowseComp-ZH (Zhou et al., 2025) is a high-difficulty benchmark developed to evaluate the web browsing and reasoning capabilities of large language models (LLMs) within the Chinese information ecosystem. Recognizing that existing benchmarks like BrowseComp focus primarily on English-language contexts, BrowseComp-ZH addresses the unique challenges posed by the Chinese web, including linguistic complexity, fragmented information across diverse platforms, and varying search engine infrastructures. The benchmark comprises 289 multi-hop questions spanning 11 diverse domains such as film, art, medicine, geography, history, and technology. Each question is meticulously reverse-engineered from a concise, objective, and easily verifiable answer (e.g., a date, number, or proper noun). A two-stage quality control protocol ensures high question difficulty and answer uniqueness. Notably, the questions are designed so that answers are not readily retrievable via standard search engines, requiring models to engage in complex reasoning and information synthesis.

**Humanity's Last Exam (HLE)** (Phan et al., 2025) is a multi-modal benchmark designed to evaluate the reasoning and problem-solving capabilities of large language models (LLMs) across a broad spectrum of academic disciplines. Developed collaboratively by the Center for AI Safety and Scale AI, HLE comprises 3,000 expert-crafted questions spanning mathematics, humanities, natural sciences, and more. Unlike BrowseComp and BrowseComp-ZH, where agents can locate and answer questions by analyzing information retrieved from the web, HLE presents 'closed-book' academic challenges (the answers aren't directly available online) that demand deep reasoning and specialized domain expertise, going well beyond what surface-level online searches can support. Each question in HLE is designed to be unambiguous and verifiable, yet not readily answerable through internet search, thereby testing the intrinsic reasoning abilities of LLMs.

# **B** Open-Source Deep Research Implementations

Table 1: Overview of open-source deep research implementations.

Name	Base Model	Optimization	Training Data	Evaluation Data	Link
Agentic Reasoning (Wu et al., 2025)	N/A	Prompt	N/A	GPQA	Link
Search-o1 (Li et al., 2025b)	Qwen	Prompt	N/A	GPQA, MATH500, AMC2023, AIME2024, LiveCodeBench, Natural Questions, TriviaQA, HotpotQA, 2Wiki, MuSiQue, Bamboogle	Link
Open Deep Search (Alzubi et al., 2025)	DeepSeek, Llama	Prompt	N/A	SimpleQA, FRAME	Link
Search-R1 (Jin et al., 2025)	Llama, Qwen	RL	NQ, HotpotQA	NQ, TriviaQA, PopQA, HotpotQA, 2WikiMultiHopQA, MuSiQue, Bamboogle	Link
DeepResearcher (Zheng et al., 2025a)	Qwen	RL	NQ, TQ, HotpotQA, 2WikiMultiHopQA	MuSiQue, Bamboogle, PopQA, NQ, TQ, HotpotQA, 2WikiMultiHopQA	Link
R1-Searcher (Song et al., 2025)	Llama, Qwen	RL	HotpotQA, 2WikiMultiHopQA	HotpotQA, 2WikiMultiHopQA, MuSiQue, Bamboogle	Link
ReSearch (Chen et al., 2025a)	Qwen	RL	MuSiQue	HotpotQA, 2WikiMultiHopQA, MuSiQue, Bamboogle	Link
ZeroSearch (Sun et al., 2025a)	Llama, Qwen	RL	NQ, HotpotQA	NQ, TriviaQA, PopQA, HotpotQA, 2WikiMultiHopQA, MuSiQue, Bamboogle	Link
IKEA (Huang et al., 2025b)	Qwen	RL	NQ, HotpotQA	NQ, HotpotQA, PopQA, 2Wikimultihopqa	Link
Webthinker (Li et al., 2025c)	Qwen	RL	SuperGPQA, WebWalkerQA OpenThoughts, NaturalReasoning, NuminaMath	, GPQA, GAIA, WebWalkerQA, Humanity's Last Exam	Link
gpt-researcher	OpenAI Series	Prompt	N/A	N/A	Link
deep-searcher	DeepSeek, OpenAI Series, Claude, Gemini, Grok, Qwen, Llama, GLM	Prompt	N/A	N/A	Link
nanoDeepResearch	OpenAI Series, Claude	Prompt	N/A	N/A	Link
DeerFlow	OpenAI Series, Qwen	Prompt	N/A	N/A	Link
deep-research	DeepSeek, OpenAI Series	Prompt	N/A	N/A	Link
open-deep-research	OpenAI Series, DeepSeek, Claude, Gemini	Prompt	N/A	N/A	Link
r1-reasoning-rag	DeepSeek	Prompt	N/A	N/A	Link
node-DeepResearch	Gemini, OpenAI Series	Prompt	N/A	N/A	Link
deep-research	Gemini, OpenAI Series, DeepSeek, Claude, Grok	Prompt	N/A	N/A	Link