

WebWatcher: Breaking New Frontiers of Vision-Language Deep Research Agent

Xinyu Geng*, Peng Xia*, Zhen Zhang*, Xinyu Wang^(✉), Qiuchen Wang, Ruixue Ding, Chenxi Wang, Jialong Wu, Yida Zhao, Kuan Li, Yong Jiang^(✉), Pengjun Xie, Fei Huang, Jingren Zhou

Tongyi Lab , Alibaba Group



<https://github.com/Alibaba-NLP/WebAgent>

Abstract

Web agents such as Deep Research have demonstrated superhuman cognitive abilities, capable of solving highly challenging information-seeking problems. However, most research remains primarily text-centric, overlooking visual information in the real world. This makes multimodal Deep Research highly challenging, as such agents require much stronger reasoning abilities in perception, logic, knowledge, and the use of more sophisticated tools compared to text-based agents. To address this limitation, we introduce WebWatcher, a multimodal Agent for Deep Research equipped with enhanced visual-language reasoning capabilities. It leverages high-quality synthetic multimodal trajectories for efficient cold start training, utilizes various tools for deep reasoning, and further enhances generalization through reinforcement learning. To better evaluate the capabilities of multimodal agents, we propose BrowseComp-VL, a benchmark with BrowseComp-style that requires complex information retrieval involving both visual and textual information. Experimental results show that WebWatcher significantly outperforms proprietary baseline, RAG workflow and open-source agents in four challenging VQA benchmarks, which paves the way for solving complex multimodal information-seeking tasks.

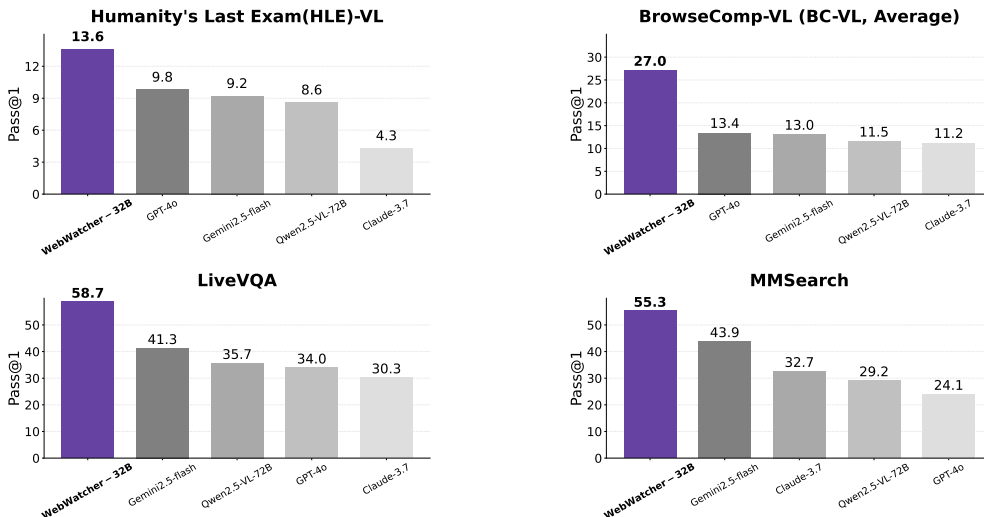


Figure 1: Overall performance of WebWatcher compares to other models across four benchmarks. All other models are equipped with RAG workflow.

*Equal Core Contributors. Xinyu Geng, Zhen Zhang and Xinyu Wang are project leaders.

^(✉)Corresponding author. {tomas.wxy, yongjiang.yj}@alibaba-inc.com

1 Introduction

Deep research agents represents a new frontier in Artificial Intelligence (AI), where Large Language Models (LLMs) go beyond static prompts to plan multi-step tasks: issuing search queries, reading documents, browsing the web, and refining answers through iterative reasoning (OpenAI, 2025a; Google, 2024; Perplexity, 2025). Many open-source, text-only web agents for deep research (Li et al., 2025b;a; Wu et al., 2025a; Zheng et al., 2025) have demonstrated superhuman abilities to interact with intricate information environments, achieving remarkable performance on high-difficulty benchmarks such as BrowseComp (Wei et al., 2025a) and Humanity’s Last Exam (HLE) (Phan et al., 2025). However, most advances to date remain primarily text-centric, neglecting the rich visual information omnipresent in real-world scenarios. Many research-centric and everyday tasks such as interpreting scientific diagrams (Hu et al., 2024), analyzing graphics (Wang et al., 2024b), or navigating visually rich web interfaces (Hong et al., 2024), demand integrated vision-language reasoning (Dong et al., 2025). While proprietary agents have made strides in this area, multimodal deep research remains largely unexplored, with few agents tackling high-difficulty Vision-Language (VL) tasks (Xu & Peng, 2025; Hu et al., 2025).

The key challenge lies that current multimodal deep research agents rely on rigid, template-driven pipelines limited to specific scenarios, lacking the flexible reasoning required for real research challenges. On the one hand, many existing VL Agents rely mainly on visual tools to perform image-based reasoning, such as optical character recognition (OCR), bounding box extraction, image cropping, visual annotation and so on (Zhao et al., 2025; Su et al., 2025a;b). While visual tools assist agents in handling perceptual tasks, they struggle to integrate visual reasoning with deep textual understanding and cross-modal inference, falling short in tackling high-difficulty tasks that require complex reasoning. As shown in Fig. 2, when faced with a high-difficulty case from GAIA (Mialon et al., 2023), visual-only analysis fails to yield a solution, highlighting that VL Agents remain confined to perception tasks. On the other hand, only use search tools restricts Search Agents to retrieval tasks and prevents them from solving complex real-world tasks (Wu et al., 2025b). Although retrieval-augmented reasoning can handle many knowledge-based questions, it often fails when answers are implicit, require structured interactions, or demand additional computation (Shen et al., 2024; Gu et al., 2025). For example, some problems require executing code to interpret charts, performing step-by-step calculations, or browsing dynamic webpages to extract up-to-date or structured content. As illustrated in Fig. 2, solving this case requires not only searching, but also tools to click through relevant links and browse the resulting webpage to gather necessary information.

To address this gap, agents for VL deep research require not only **strong reasoning abilities across both textual and visual information**, but also **effective use of multiple external tools**. Thus, we introduce **WebWatcher**, a VL web agent with deep research capability.

In order to achieve strong reasoning abilities across both textual and visual information, it is essential to construct data that combine high-quality visual content with complex reasoning. However, most current visual question answering (VQA) data primarily focus on visual perception with single-step inference, lacking planning complexity and reasoning depth needed to support advanced agent capabilities (Chen et al., 2024; Li et al., 2025c). Thus, we introduce a pipeline to generate training data that benefits in-depth, multi-step reasoning and strategic planning, encouraging agents to synthesize information across both modalities. Importantly, we begin by harvesting real-world knowledge via random walks over diverse web sources to build high-difficulty question answering (QA) examples with unpredictable, multi-hop reasoning chains (Wu et al., 2025a; Li et al., 2025a), closely resembling the information-seeking and compositional nature of BrowseComp tasks (Wei et al., 2025b). To further raise the complexity, we mask key entities in questions, replacing specific terms with generic description, forcing models to infer relationships from context. Next, we convert this enriched QA pairs into multimodal VQA items using an adaptable QA-to-VQA pipeline compatible with most existing QA datasets, enabling substantial scaling of multimodal datasets. Finally, a multi-stage filtering process ensures the quality and clarity of the

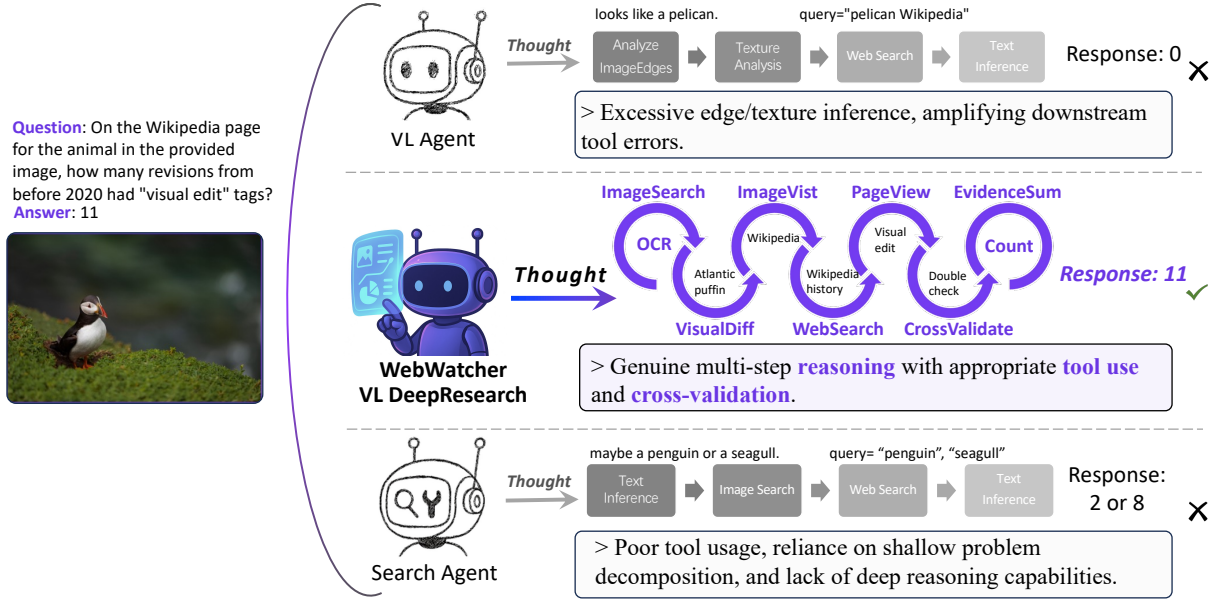


Figure 2: Comparison of VL reasoning agents. WebWatcher resolves the GAIA case that defeats either vision-only reasoning or search-based agents, demonstrating the strength of multi-tool integration and in-depth reasoning generalization.

generated data.

Moreover, to enable effective use of multiple external tools, first we implement the integration of multiple tools, including Web Image Search, Web Text Search, Webpage Visit, Code Interpreter and internal OCR. However, a key challenge lies in obtaining high-quality reasoning trajectories. Firstly, recent reasoning agents generate traces that often tend to be long and templated, with limited diversity or adaptability across tasks (Rose et al., 2023; Bi et al., 2025). Secondly, coordinating multiple tools, each of which has distinct input-output formats and reasoning roles, makes trajectory construction even more complex. To address this, we develop a fully automated pipeline that uses prompting to construct reasoning trajectories from action-observation sequences. Unlike hand-crafted CoT-style traces or template-based rationales, our trajectories are grounded in actual tool-use behavior and reflect procedural decision-making aligned with complex reasoning demands. We also combine LLM-based prompting with rule-based filtering to ensure high-quality. Then we finetune the agent model using synthesized high-quality trajectories that reflect deep reasoning across tools, and further optimize it via reinforcement learning algorithm, GRPO (Shao et al., 2024).

Finally, we introduce a challenging VQA benchmark **BrowseComp-VL**, which mirrors the complexity of BrowseComp, but extends it into the visual domain, emphasizing challenges that demand both perception and superhuman information-gathering abilities. Queries are constructed to be long, BrowseComp-style, and entity-obfuscated, requiring agents to perform cross-modal inference, thorough information-seeking, and high-level planning to resolve. Perception alone is not sufficient. Agents need to use external tools such as web search, image retrieval and webpage browsing to gather and integrate evidence.

As shown in Fig.1, **WebWatcher** achieves strong performance on several high-difficulty benchmarks, including HLE, LiveVQA, BrowseComp-VL, and MMSearch. It consistently outperforms existing open-source multimodal research agents and proprietary systems on four reasoning benchmarks, and show a competitive performance on the perception benchmark, SimpleVQA.

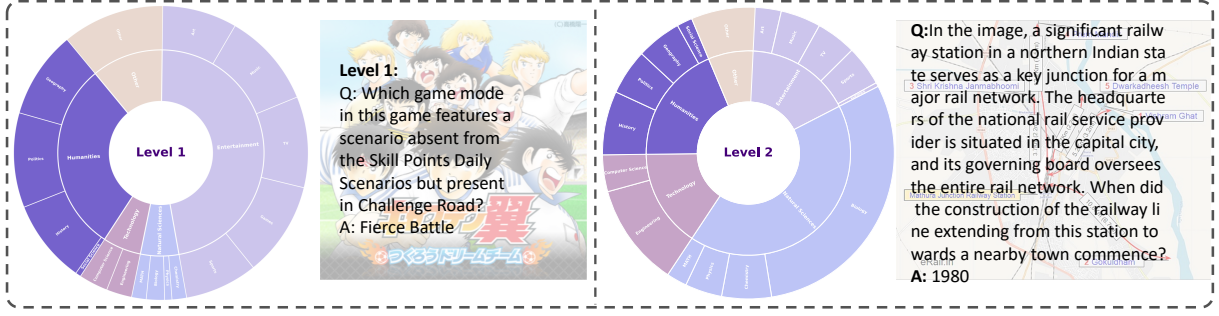


Figure 3: Domain Distribution for Level 1 and Level 2.

2 Data Preparation

In this section, we introduce our dataset construction methodology, emphasizing high data quality, multi-step multimodal reasoning, and robust compatibility with web-based agent paradigms.

2.1 Dataset Overview and Structure

Our dataset **BrowseComp-VL** is designed for advanced multi-modal reasoning agents operating in real-world web environments. Each example comprises a factual image, an associated question requiring cross-modal reasoning, and auxiliary metadata about the underlying entities and relations. As shown in Fig.3, BrowseComp-VL is organized into 5 major domains comprising 17 fine-grained subfields, which is detailed in Appendix B. The major domains include *Entertainment*, *Humanities*, *Technology*, *Natural Science* and *Other*. Additionally, we define two difficulty levels to encourage a spectrum of reasoning abilities:

- **Level 1:** Questions require multi-hop reasoning but still reference explicit entities. While the answers can be obtained through iterative retrieval steps, the reasoning process remains non-trivial due to the need for integrating information across multiple sources.
- **Level 2:** Questions are constructed with intentionally obscured or fuzzified entities and attributes. For example, concrete dates are replaced with vague periods, names are masked, and quantitative properties are fuzzed up. This design introduces substantial uncertainty, requiring the agent to plan, compare, and synthesize information rather than perform direct retrieval.

Prompting LLMs to generate VQA questions directly from images is a common practice, but it often yields shallow, single-hop queries that lack ambiguity, structured planning, and deeper reasoning. Moreover, most existing VQA datasets focus on perception and rarely combine rich textual information with knowledge-intensive, multi-step reasoning. To address this limitation, we first build a diverse set of challenging textual QA pairs focused on multi-hop reasoning and knowledge-intensive questions. Then we transform these into VQA tasks by grounding them in relevant visual content. This pipeline yields high-quality multimodal data maintained both visual richness and textual reasoning complexity.

2.2 VQA Pairs Construction

2.2.1 Generate QA

Level 1 Inspired by the CRAWL-QA from WebDancer (Wu et al., 2025a), we increase the depth and breadth of reasoning by collecting root URLs from authoritative and knowledge-rich sources such as *arXiv*, *GitHub*, and *Wikipedia*. To emulate human-like browsing behavior, we recursively traverse accessible hyperlinks within each root domain. GPT-4o is then used to synthesize question-answer pairs from the aggregated content.

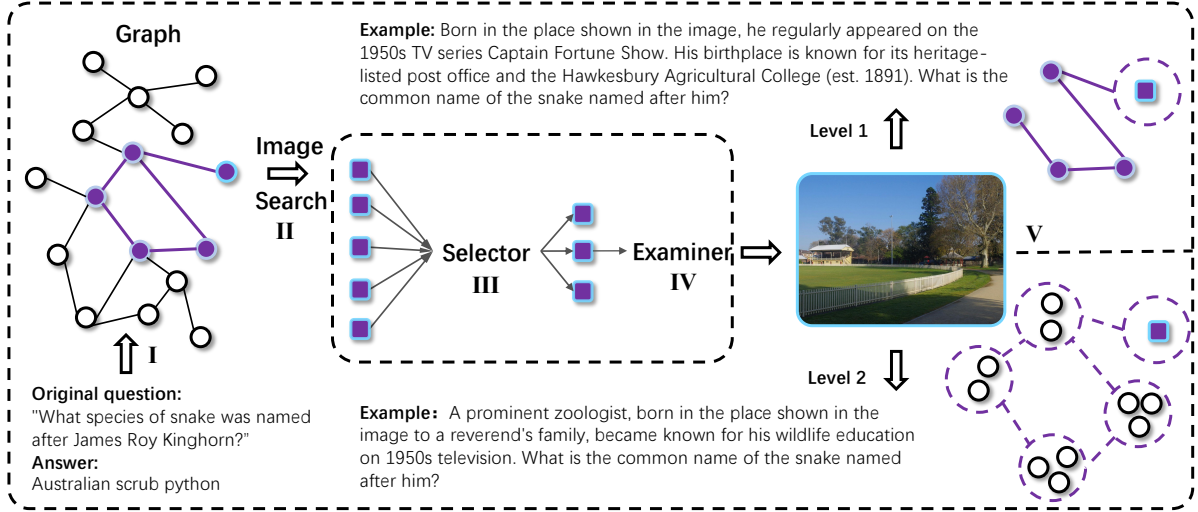


Figure 4: Data generation pipelines.

Level 2 Following WebSailor (Li et al., 2025a), we construct queries with fuzzed entities by replacing precise references with partial, ambiguous descriptions. Our approach emphasizes situations where answers cannot be retrieved through direct lookup, but instead require contextual reasoning and synthesis across modalities.

We design a two-stage generation framework consisting of:

- (1) **Nodes Selecting:** Given an initial *Wikipedia* page, we first prompt GPT-4o (OpenAI, 2024) to generate a base QA pair grounded in the page content. The title of page serves as the root entity node B_{root} . Starting from B_{root} , we recursively expand a hyperlink graph by traversing outgoing links to construct a tree of depth d and branching factor k , resulting in a total of $(k^{d+1} - 1) / (k - 1)$ nodes in the entire traversal. In our implementation, we set $d = 3$ and $k = 3$ to ensure sufficient semantic coverage.
To generate diverse reasoning paths, we sample multiple subgraphs from the entire tree. We randomly select a subset of nodes and continue expansion until a subgraph containing N entities is formed. Each subgraph defines a unique reasoning path from B_{root} to a newly selected target entity B , forming a knowledge graph encoding multi-hop relations. These subgraphs serve as the foundation for generating distinct QA pairs.
- (2) **Query Generating:** Based on the selected subgraph and the ground truth, we first prompt GPT-4o to generate a standard form that explicitly references entities and relations along the reasoning path. Then, it is transformed into a fuzzed version in which key references are replaced with partial, ambiguous, or qualitative descriptions. This design encourages diverse reasoning patterns, pushing models to infer answers via synthesis rather than surface matching.

2.2.2 QA-to-VQA Conversion

Visual Context Construction for VQA To ensure effective visual grounding, we first filter out trivial or excessively ambiguous target entities B , such as those that denote temporal references or domain-external concepts, which lack sufficient visual grounding. For each retained entity \hat{B} , we retrieve a set of web images $\mathcal{I}(\hat{B}) = I_1^{\hat{B}}, I_2^{\hat{B}}, \dots, I_K^{\hat{B}}$ via Google SerpApi (Google, 2025), where $K = 2$ in our implementation. The resulting images $\mathcal{I}(\hat{B})$ serve as the visual grounding to construct multimodal reasoning examples. Unlike synthetic or composited images prevalent in existing VQA benchmarks, our images are strictly authentic, thus minimizing noise and maximizing relevance for real-world tasks.

Entity Masking and Question Transformation To construct image-grounded VQA pairs from each textual QA instance (q_t, a) , we apply prompt-based rewriting using GPT-4o. Let q_t denote the original text question containing a clear mention of the target entity \hat{B} . We mask this mention with a visual reference token r_{vis} , such as demonstratives (“this entity”) or descriptive phrases (“the object in the image”), to yield a transformed VQA query q . Simultaneously, we generate an image query string $s_{\text{img}}(\hat{B})$ to guide filtering of $\mathcal{I}(\hat{B})$. Each image $I_k^{\hat{B}} \in \mathcal{I}(\hat{B})$ is then paired with (q, a) to form a distinct VQA instance. Consequently, each textual QA pair produces K multimodal examples, yielding a total of Kn VQA items from n original questions.

2.3 Quality Control

To ensure high-quality VQA samples, we employ a three-stage filtering pipeline including a selector and an examiner:

- **Selector:** First, we eliminate data where the transformed VQA query q is same as original question q_t , and discard cases where the entity name \hat{B} or its aliases appear explicitly in q_t , suggesting a failure in entity masking or question rewriting. Second, GPT-4o is prompted to evaluate each image $I_k^{\hat{B}} \in \mathcal{I}(\hat{B})$ with respect to both the original QA pair (q_t, a) and the transformed VQA query (q, a) . GPT-4o assesses contextual alignment, semantic fit, and the plausibility of visual reasoning. Instances receiving low relevance scores are filtered out.
- **Examiner:** For each retained image-query pair $(s_{\text{img}}(\hat{B}), \mathcal{I}(\hat{B}))$, GPT-4o is prompted to answer the synthesized query $s_{\text{img}}(\hat{B})$ using only the visual content and associated captions of $\mathcal{I}(\hat{B})$. Failure to answer accurately indicates weak retrieval or a poorly formed image query, and such query q are therefore filtered out.

Additionally, to mitigate false negatives arising from missing world knowledge, the model is granted access to available image captions during validation.

3 Trajectory Generation and Post-Training

We use supervised fine-tuning (SFT) as a cold start to teach the agent tool-augmented reasoning, based on high-quality ReAct-style (Yao et al., 2023) trajectories generated by an automated pipeline. Reinforcement learning is then applied to further optimize tool use and decision-making.

3.1 Automated Generation of Reasoning Trajectories

3.1.1 Multimodal Tools

We equip WebWatcher with a set of external tools, including: (1) **Web Image Search** powered by Google SerpApi (Google, 2025), for retrieving relevant image, corresponding caption and its webpage url to better understanding input image I ; (2) **Web Text Search**, for open-domain information seeking, retrieving title and webpage url of query (Google, 2025); (3) **Visit** from Jina (Jina.ai, 2025), enabling navigation to specific URLs for summary of the webpages, tailored to the "goal" specified in the LLM’s action; (4) **Code Interpreter**, supporting symbolic computation and numerical reasoning (Cheng et al., 2024). (5) **OCR**, an internal tool invoked via prompt and SFT data to extract text from the input image. Full implementation details are provided in Appendix D.

3.1.2 Automated Trajectory Annotation

Given a VQA instance (I, q, a) from BrowseComp-VL, we employ GPT-4o to automatically construct tool-use trajectories that simulate how a human might explore and reason through a problem by trying different tools step by step. Following ideas from ReAct (Yao et al., 2023), each trajectory τ consists of

multiple *think-act-observe* cycles. Concretely, at each iteration t , the language model takes as input the accumulated context history and generates:

- a **Thought**: the agent’s intermediate reasoning or plan, enclosed in `<think>...</think>`;
- an **Action**: the tool invocation wrapped in `<tool_call>...</tool_call>` and the final answer enclosed in `<answer>...</answer>`;
- an **Observation**: the returned result from the environment, within `<tool_response>...</tool_response>` tags.

The action space T includes a discrete set of tool-use actions t_l , allowing the agent to retrieve external information, navigate webpages, and perform computations, etc. Crucially, the Finish action signals task completion by returning a final answer and terminating the reasoning episode.

Formally, a trajectory of length L is denoted as

$$\tau = \{(t_0, o_0), (t_1, o_1), \dots, (t_L, o_L)\}, \quad (1)$$

where each action $t_i \in \mathcal{T}$ and each observation o_i reflects the resulting environment feedback after tool execution. The trajectory serves as a content-grounded demonstration of planning and tool selection.

3.1.3 Trajectory Filtering and Quality Assurance

To ensure robust and instructive supervision, we apply three-stage trajectory selection:

- (1) **Final Answer Matching** We retain trajectory τ where the final answer matches the ground truth a , ensuring that the entire sequence of tool-use steps leads to a correct and complete solution.
- (2) **Step-by-Step Consistency Check** We use GPT-4o to verify the logical consistency of each intermediate step in trajectory τ . Each pair (t_l, o_l) is reviewed to ensure the tool call and observation align with the context and reasoning goal. Trajectories with hallucinated content, contradictions, or unjustified tool calls are discarded. This avoids the common failure mode where correct answers are reached by lucky guessing rather than meaningful tool use.
- (3) **Minimum Tool Usage Requirement** To encourage multi-step reasoning rather than shortcutting, we remove τ with fewer than three tool calls. This ensures that training data reflects substantive, process-driven interactions rather than trivial or one-step completions.

3.2 Supervised Fine-Tuning as Cold Start

After filtering, the resulting dataset consists of K high-quality tool-use trajectories. For each step l of the i -th trajectory, WebWatcher is trained to predict the correct tool-use action $t_l^{(i)}$, based on the input image $I^{(i)}$, question $q^{(i)}$, and all previous actions and observations $(t_{<l}^{(i)}, o_{<l}^{(i)})$. As shown in Eq. 2, SFT maximizes the log-likelihood of the target action $t_l^{(i)}$:

$$\max_{\theta} \sum_{i=1}^K \sum_{l=1}^{L_i} \log P_{\theta} \left(t_l^{(i)} | I^{(i)}, q^{(i)}, t_{<l}^{(i)}, o_{<l}^{(i)} \right), \quad (2)$$

where θ denotes model parameters.

As a cold-start stage, SFT teaches the agent to use tools meaningfully and follow structured, multi-step reasoning processes.

3.3 Reinforcement Learning

With SFT providing a cold-start initialization, we employ Group-Relative Policy Optimization (GRPO) (Guo et al., 2025), a ranking-based variant of PPO, to further refine decision-making and adapt to complex

tasks. Specifically, for the VQA query q , the current policy π_θ generates a group $G = \{\tau_1, \dots, \tau_K\}$ of K complete trajectories, each assigned a scalar return R_i . The group-relative advantage is in Eq. 3:

$$A_{\text{rel}}(\tau^{(i)}) = R^{(i)} - \frac{1}{K} \sum_{j=1}^K R^{(j)}, \quad (3)$$

which normalizes rewards within the group and eliminates the reliance on a separate value function. The GRPO objective is defined as a clipped surrogate loss:

$$\mathcal{L}_{\text{GRPO}}(\theta) = \mathbb{E}_{\tau^{(i)} \in \mathcal{G}} \left[\min \left(\rho^{(i)} A_{\text{rel}}(\tau^{(i)}), \text{clip} \left(\rho^{(i)}, 1 - \epsilon, 1 + \epsilon \right) A_{\text{rel}}(\tau^{(i)}) \right) \right] - \beta D_{\text{KL}}(\pi_\theta \| \pi_{\theta_{\text{old}}}), \quad (4)$$

where $\rho^{(i)} = \frac{\pi_\theta(\tau^{(i)})}{\pi_{\theta_{\text{old}}}(\tau^{(i)})}$ is the importance sampling ratio between the current and previous policy, $A_{\text{rel}}(\tau^{(i)})$ is the group-relative advantage defined in Eq. 3, ϵ is the clipping threshold, and D_{KL} denotes the Kullback–Leibler divergence between successive policies. The coefficient β controls the strength of the KL penalty. This objective promotes stable updates while encouraging exploration of trajectories with higher relative return.

Each trajectory τ is a sequence of L tool calls $\tau = \{(t_0, o_0), (t_1, o_1), \dots, (t_L, o_L)\}$. The trajectory τ first receives a binary format score $r_f \in \{0, 1\}$, which is 1 if all tool calls conform to the schema. Then, an LLM grader provides a semantic accuracy score $r_a \in [0, 1]$ by comparing the final answer with the ground truth.

The total reward R for τ is computed as:

$$R = w r_f + (1 - w) r_a, \quad (5)$$

where $w = 0.2$ denotes the weight balancing r_f and r_a , encouraging the agent to generate well-structured tool calls while ultimately focusing on task completion. Since R is assigned only once at the end of each episode, the group-relative ranking in Eq. 3 facilitates effective credit assignment without relying on per-step shaping. In our GRPO implementation, we collect rollouts in groups of $N = 16$ trajectories, which provides sufficient diversity for computing meaningful relative advantages while maintaining computational efficiency during training.

4 Experiments

4.1 Setup

Training Data Construction Our training data have three sources: (1) The training set of BrowseComp-VL, (2) long-tail QA pairs converted into VQA format, and (3) hard VQA samples. Firstly, we construct the BrowseComp-VL training set with 110,000 Level-1 and 70,000 Level-2 QA pairs. After VQA conversion and filtering, 60,000 Level-1 and 40,000 Level-2 high-quality examples are retained. Secondly, the long-tail QA data are sampled from training instances sharing a similar distribution with SimpleVQA, which transformed into 5,000 VQA examples. Thirdly, hard examples are drawn from InfoSeek (Chen et al., 2023), VQAv2.0 (Goyal et al., 2017), LogicVista (Xiao et al., 2024), and Encyclopedic VQA (Mensink et al., 2023). Specifically, (Huang et al., 2025) is added to activate internal OCR. We apply rejection sampling through GPT-4o to ensure perceptual difficulty. After trajectory generation and filtering pipeline, the SFT training set is constructed with 8,000 high-quality tool-use trajectories. An additional 2,000 VQA samples are reserved for GRPO. The final ratio of data sources is 5:3:2 for BrowseComp-VL, long-tail VQA, and hard VQA data, respectively.

Models and Benchmarks We perform SFT and RL training on Qwen2.5-VL-7B and Qwen2.5-VL-32B. We evaluate our method on five challenging benchmarks: BrowseComp-VL, HLE (Phan et al., 2025), LiveVQA (Fu et al., 2025), SimpleVQA (Cheng et al., 2025) and MMSearch (Jiang et al., 2024). The detailed introduction of these benchmarks is in Appendix D.4.

Table 1: Main results on HLE.

Backbone	Humanity’s Last Exam (HLE-VL)								
	Bio.	Chem.	CS/AI	Engineer.	Human.	Math	Physics	Other	Avg.
<i>Direct Inference</i>									
GPT-4o	13.8	0.0	0.0	3.9	12.0	6.8	7.1	7.0	6.5
Gemini-2.5-flash	12.1	1.6	0.0	0.0	4.0	0.0	14.3	0.0	4.9
Claude-3.7-Sonnet	1.7	4.8	0.0	2.0	0.0	0.0	0.0	12.3	2.8
Qwen-2.5-VL-7B	3.4	3.2	7.1	0.0	4.0	2.3	7.1	0.0	2.6
Qwen-2.5-VL-32B	3.4	6.5	0.0	3.9	8.0	2.3	7.1	0.0	3.7
Qwen-2.5-VL-72B	3.4	8.0	0.0	5.9	8.0	0.0	0.0	7.0	4.9
<i>RAG Workflow</i>									
GPT-4o	9.8	24.1	4.8	0.0	2.0	4.0	9.1	14.3	12.3
Gemini-2.5-flash	25.9	3.2	7.1	0.0	8.0	9.1	3.5	14.0	11.4
Claude-3.7-Sonnet	4.3	5.2	4.8	0.0	0.0	0.0	9.1	14.3	3.5
Qwen-2.5-VL-7B	4.3	6.9	3.2	7.1	0.0	4.0	4.5	7.1	5.3
Qwen-2.5-VL-32B	5.2	10.3	3.2	7.1	0.0	0.0	4.5	7.1	8.8
Qwen-2.5-VL-72B	15.8	10.3	8.1	0.0	2.0	8.0	6.8	14.3	8.6
<i>Reasoning Model</i>									
o4-mini	12.1	23.7	17.7	0.0	5.8	0.0	33.3	21.4	16.0
Gemini-2.5-Pro	23.7	17.7	13.3	11.5	8.0	13.3	14.3	15.5	15.8
<i>Open Source Agents</i>									
OmniSearch (GPT-4o)	15.5	8.2	0.0	2.2	8.0	6.8	21.4	12.1	9.3
WebWatcher-7B	18.6	6.5	6.7	7.7	4.0	6.7	7.1	17.2	10.6
WebWatcher-32B	33.8	9.7	0.0	5.8	8.0	8.9	14.3	13.8	13.6

Baselines We compare our method with the following paradigms:

- **Direct Inference:** Models directly generate answers using internal knowledge without external retrieval or planning. We evaluate GPT-4o (OpenAI, 2024), Gemini-2.5-flash (DeepMind, 2025), Claude-3.7-Sonnet (Anthropic, 2025), and Qwen-2.5-VL family (7B/32B/72B) (Bai et al., 2025).
- **RAG Workflow:** Two-stage models first retrieve relevant information and then generate answers. We evaluate GPT-4o, Gemini-2.5-Flash, Claude-3.7-Sonnet, and Qwen-2.5-VL variants (7B/32B/72B) under this paradigm.
- **Reasoning Baselines:** OmniSearch (Li et al., 2025c) is a search-oriented reasoning agents, whose base model is GPT-4o. Gemini-2.5-Pro and o4-mini (OpenAI, 2025b) represent multi-step reasoning.

Metric and Hyper-parameters We repeatedly generate for k times to generate pass@ k (Chen et al., 2021), with temperature of 0.6 and top-p of 0.95. The pass@1 score is computed as: $\text{pass@1} = \frac{1}{n} \sum_{i=1}^n p_i$, where p_i is the binary correctness of the i -th prediction. Answer correctness is judged using the *LLM-as-Judges* approach (Liu et al., 2024; Wang et al., 2024a).

4.2 Main Results

Results on HLE. As shown in Tab. 1, different frameworks exhibit large performance gaps on the demanding Humanity’s Last Exam (HLE) benchmark. Models with direct inference consistently underperform, with average scores below 10%. This highlights the inherent limitations of vanilla MLLMs when faced with complex, knowledge-intensive VQA settings requiring cross-modal reasoning and external information integration. RAG-based approaches show moderate improvements overall, especially for specific subfields such as Chemistry. Reasoning-specialized models like Gemini-2.5-Pro and o4-mini attaining average scores of 15.8 and 16.0 respectively. Notably, our proposed WebWatcher-32B achieves a new state-of-the-art result, reaching an average score of 18.2%, and surpasses the strong GPT-4o based

Table 2: Main results on four challenging benchmarks. Avg. signifies the average score of three inference runs.

Backbone	BC-VL			LiveVQA	MMSearch	SimpleVQA
	Level1	Level2	Avg.			
Direct Inference						
GPT-4o	6.4	4.0	5.5	29.7	18.7	47.0
Gemini-2.5-flash	11.6	6.0	9.6	35.0	19.6	63.0
Claude-3.7-Sonnet	8.8	4.0	7.1	23.7	12.3	42.7
Qwen-2.5-VL-7B	0.8	0.0	0.5	22.7	4.09	30.7
Qwen-2.5-VL-32B	3.2	1.0	2.4	26.3	7.60	40.7
Qwen-2.5-VL-72B	9.2	3.0	7.1	30.3	11.7	51.3
RAG Workflow						
GPT-4o	16.8	7.0	13.4	34.0	24.1	61.6
Gemini-2.5-flash	15.2	9.0	13.0	41.3	43.9	68.6
Claude-3.7-Sonnet	13.9	6.0	11.2	30.3	32.7	59.3
Qwen-2.5-VL-7B	3.6	1.0	2.7	21.7	9.94	21.0
Qwen-2.5-VL-32B	9.4	3.0	7.2	30.5	17.5	44.6
Qwen-2.5-VL-72B	14.4	6.0	11.5	35.7	29.2	58.6
Open Source Agents						
OmniSearch (GPT-4o)	19.7	10.0	16.3	40.9	49.7	63.0
WebWatcher-7B	23.6	17.0	21.2	51.2	49.1	54.3
WebWatcher-32B	28.4	25.0	27.0	58.7	55.3	59.0

Omnisearch baseline by a substantial margin. Moreover, WebWatcher-32B demonstrates particularly significant gains in challenging domains such as Biology and Physics, underscoring the effectiveness and broad applicability of our agentic approach for solving real-world, open-domain, high-stakes exams.

Results on Four Challenging Benchmarks. Results in Tab. 2 highlight the comparative advantages of WebWatcher across four challenging VQA benchmarks. While direct inference methods with strong MLLMs remain limited, and RAG workflows offer consistent improvement, especially on LiveVQA and SimpleVQA, our agentic system shows clear superiority. Among these, our proposed WebWatcher-32B stands out, delivering top-tier performance with 58.7% on LiveVQA, 55.3% on MMSearch, and highly competitive results on the other two datasets. Compared to both RAG-based and previous agentic baselines such as OmniSearch, WebWatcher achieves more stable and superior results, particularly on demanding, real-world visual search benchmarks like MMSearch. Furthermore, the BrowseComp-VL benchmark is purposely difficult, requiring multi-page web browsing plus fine-grained visual grounding, and most baselines stay below 20%, underscoring the benefit of our dynamic tool-use loop. Even on SimpleVQA, which mainly tests fine-grained visual perception and reasoning rather than external knowledge, WebWatcher attains a leading score of 52.6%. This demonstrates that our approach not only excels at knowledge-intensive tasks but also exhibits robust visual reasoning capabilities, highlighting its broad applicability across diverse VQA scenarios.

4.3 Analysis

Number of Tool Calls. Fig. 5 contrasts the share of calls to each tool with the unique demands of every benchmark. HLE involves a diverse set of tasks, including multimodal search, numerical computation, and visual reasoning, so no single tool dominates. *Web Text Search*, *Web Image Search*, and *Code Interpreter*

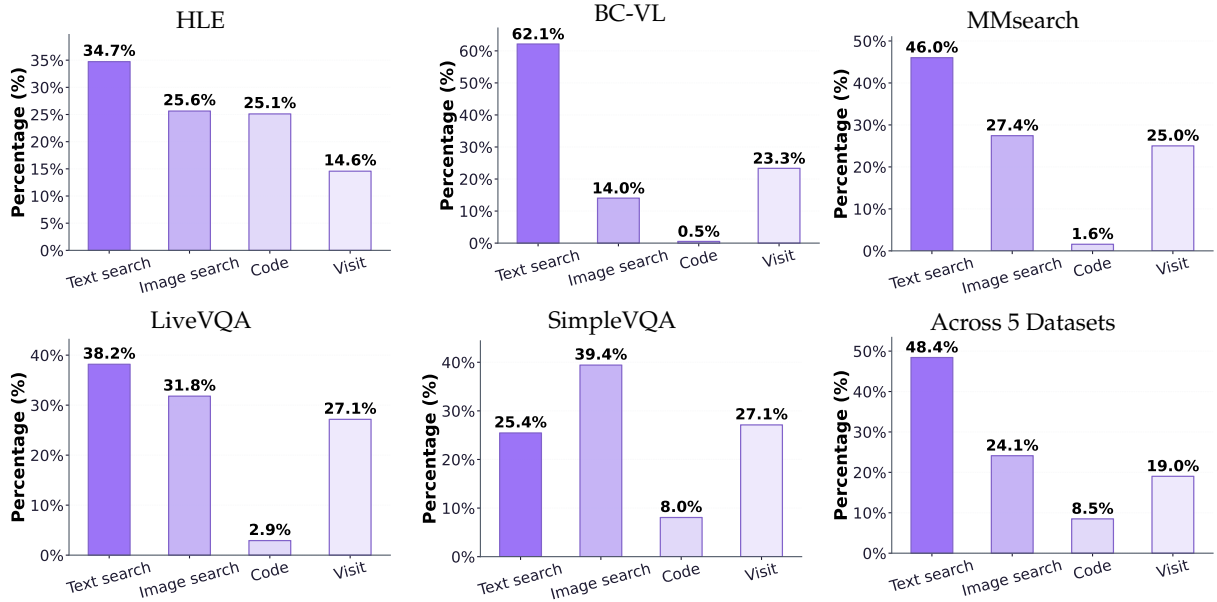


Figure 5: The percentage of tool calls in the four benchmarks. The height of each bar denotes the fraction of total calls made to that tool within the corresponding benchmark.

each account for about a quarter of all calls, with the remaining interactions mostly involving *Visit* for navigating web pages. In contrast, BrowseComp-VL focuses much more on information seeking: when information retrieval becomes the main challenge, the agent concentrates 62% of its interactions on *Web Text Search*, while *Web Image Search* is used much less and *Code Interpreter* is almost never used. LiveVQA, SimpleVQA, MMSearch shift the focus back to visual content, and the policy adapts accordingly: *Web Image Search* jumps to around one-third or more of all calls, while *Web Text Search* and *Visit* serve as auxiliary tools for textual evidence and navigation. Across all suites, the heavier *Code Interpreter* is invoked only when genuine calculation is needed, confirming that the agent is cost and context aware. Altogether, the distribution of tool usage closely tracks the characteristic skills each benchmark demands, highlighting the model’s ability to flexibly choose the right tool chain rather than defaulting to a single strategy.

Cold Start for RL Training. SFT-based cold start is indispensable for our vision-language agent, because the tasks require robust multi-hop reasoning while continuously interacting with the environment. We verify this claim by running the same online RL algorithm under two different initializations: 1) Instruct: the model is warm-started only with public instruction-following data; 2) Cold-start: before RL, the model undergoes an extra SFT stage on high-quality trajectories that explicitly demonstrate tool usage and step-by-step visual reasoning. As shown in Fig. 6, under the Instruct start the agent stays near zero for many steps of tool-call format errors wipe out the reward and the strict Qwen-2.5-72B grader further suppresses partial answers. Cold-start SFT lifts the initial scores to 0.12 on HLE, 0.30 on BC-VL, and 0.45 on LiveVQA, but the subsequent GRPO trends differ: HLE and BC-VL oscillate heavily with no clear upward drift, whereas LiveVQA shows a steady rise and keeps a 0.06–0.18 margin over the Instruct baseline throughout. Injecting CoT chains from a larger reasoner made the small model unstable, format violations, repetitions, and context overflow spiked, confirming that reasoning traces cannot replace an SFT cold start under our strict RL setting.

Pass@k Analysis on HLE. Fig. 7 plots the *Pass@k* curve of WebWatcher on HLE for k ranging from 1 to 32. Even with a single attempt ($k = 1$) the agent attains a 13.6% pass rate, already ahead of every direct-inference baseline and most retrieval-augmented systems. As k increases, the curve rises steeply at first: three diverse roll-outs raise the score to 20.3%, a relative improvement of roughly fifty percent, demonstrating that the agent can harvest substantial benefit from only a handful of complementary

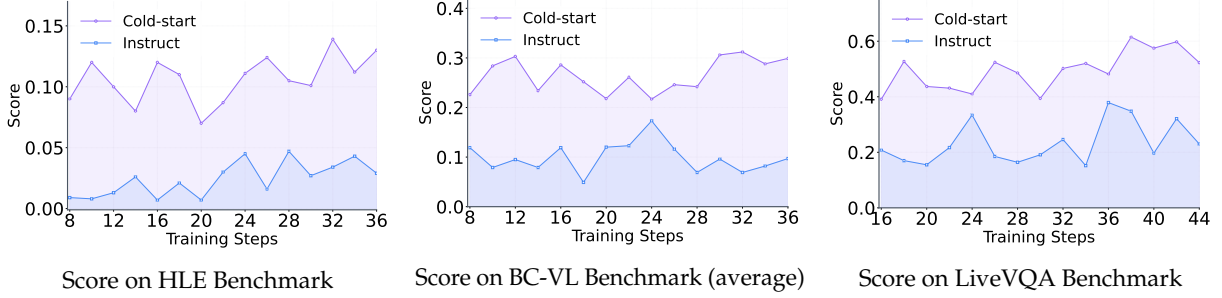


Figure 6: Performance comparison using cold start in RL training on three benchmarks.

trajectories, far more than one would obtain by merely turning up temperature on the backbone model. Improvement continues beyond $k = 8$ but at a slower pace; still, performance remains monotonically increasing, reaching 35.7% at $k = 16$ and 41.9% at $k = 32$. Thus, compared with single-shot inference, 32 trials almost quadruple the success rate and surpass reasoning models such as Gemini-2.5-Pro and o4-mini.

The smooth, jump-free shape of the curve indicates that our de-correlated sampling strategy successfully generates mutually informative trajectories rather than redundant variants, enlarging knowledge coverage and avoiding dependence on lucky outliers. Because marginal gains taper after about sixteen samples, practitioners may cap the budget at 8–16 roll-outs to secure a 2 to 3 fold accuracy boost while containing compute costs. Overall, the Pass@k profile highlights the clear advantage of the agentic paradigm: by systematically exploring and refining reasoning paths, WebWatcher delivers robust, scalable improvements on one of the most challenging open-domain multimodal exams to date.

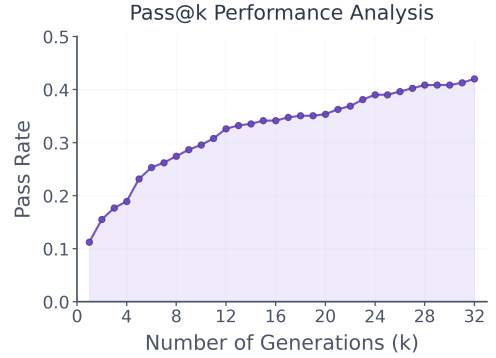


Figure 7: Pass@k performance of Web-Watcher on HLE Benchmark.

5 Related Work

Deep Research The notion of "deep research" agents—systems that autonomously search, read, reason, and synthesize knowledge from the open web—has evolved rapidly in the last two years. Proprietary solutions such as DeepResearch (OpenAI, 2025a), Gemini Deep Research (Google, 2024), now exhibit near-expert performance across fact-finding, argumentative writing, and exploratory analysis, yet the secrecy of their model architectures and data curation pipelines inhibits rigorous ablation and reproducibility. Open-source initiatives have attempted to close this gap: WebDancer (Wu et al., 2025a) introduces curriculum-driven SFT over ReAct traces. WebThinker (Li et al., 2025b) then augments SFT with policy-gradient refinement and R1-Searcher (Song et al., 2025) leverages self-play to learn tree-structured exploration policies. WebSailor (Li et al., 2025a) focuses on uncertainty reduction which used structured task obfuscation, RFT cold-start, and the DUPO algorithm. Recently, WebShaper (Tao et al., 2025) proposes a formalization-driven data-synthesis pipeline by introducing Knowledge Projections and an agentic Expander. Nevertheless, nearly all leading deep-research agents are still text-bound (Tang et al., 2025; Zhu et al., 2025). Integrating vision, layout, and cross-modal grounding is therefore not a minor tweak but the necessary next leap, multimodality will fundamentally redefine what deep research can achieve.

Multimodal VQA Benchmark Most existing VQA benchmarks primarily assess single-step perception or shallow retrieval, with limited support for integrated multimodal reasoning and planning (Chen et al., 2024; Li et al., 2025c). Datasets such as OK-VQA and A-OKVQA typically emphasize static knowledge grounding and heuristic answer prediction without requiring complex reasoning. Recent efforts have

begun to expand the evaluation space. MMT-Bench offers large-scale coverage of planning-oriented tasks across multiple domains, yet its multiple-choice format restricts the assessment of procedural reasoning and rich textual outputs (Ying et al., 2024). MicroVQA and Open3DVQA explore domain-specific and spatial reasoning, but are constrained by limited scale, manual curation, or lack of complex planning structure (Burgess et al., 2025; Zhang et al., 2025). Similarly, Dyn-VQA introduces adaptive query tasks but remains narrow in multimodal scope and size (Li et al., 2025c; Chen et al., 2025). While datasets such as MMMU and MMMU-Pro further surface performance limitations of current MLLMs on domain-specific and multi-image tasks, no existing benchmark comprehensively supports multi-step reasoning, cross-modal integration, large scale, and full automation with rigorous quality control (Yue et al., 2024a;b). To address these gaps, we introduce a large-scale, automated VQA benchmark designed to advance planning-oriented, multi-hop, and context-rich multimodal reasoning. Our dataset enables scalable evaluation of MLLMs’ capabilities in goal-directed, flexible agent behavior, setting a new standard for future research in this area.

6 Conclusion

In this work, we explore the underdeveloped landscape of multimodal DeepResearch by designing a unified framework WebWatcher that combines complex vision-language reasoning and multi-tool interaction. We present BrowseComp-VL, a challenging dataset tailored for in-depth multimodal reasoning and strategic planning, and introduce a scalable pipeline to transform complex textual QA examples into VQA. To equip agents with robust tool-use capabilities, we further develop an automated trajectory generation pipeline grounded in action-observation traces, enabling high-quality supervision for cold start and GRPO. Finally, we enhance evaluation through a test-time scaling strategy. WebWatcher establishes a strong foundation for future multimodal DeepResearch agents capable of solving real-world problems with autonomy, flexibility, and deep reasoning.

7 Acknowledgment

We sincerely thank Kuan Li for providing the LaTeX template used in the preparation of this paper.

A Symbol Definition

Table 3: Mathematical symbols and their meanings

Symbol	Meaning
B_{root}	The page title, serving as the root entity node
d	Depth of the tree
k	Branching factor of the tree
N	Number of entities contained in each subgraph
B	Newly selected target entity node
\hat{B}	Retained target entity after filtering
$\mathcal{I}(\hat{B})$	Set of web images retrieved for entity \hat{B}
$K = 2$	Number of images per entity set
(q_t, a)	Original text question and answer pair
r_{vis}	Visual reference token replacing the entity mention
q	Transformed VQA query
$s_{\text{img}}(\hat{B})$	Image query string for filtering images of \hat{B}
n	Number of original textual QA pairs
(I, q, a)	A VQA instance: image, question, and answer from BrowseComp-VL
τ	A tool-use trajectory: sequence of think-act-observe cycles
T	Discrete action space of tool-use actions
t_l	A specific tool-use action in T
\mathcal{T}	Set of all tool-use actions
L	Length of the trajectory
L_i	Length of the i -th trajectory
t_i	Action at iteration i in the trajectory ($t_i \in \mathcal{T}$)
o_i	Observation returned after executing t_i
θ	Model parameters
$G = \{\tau_1, \dots, \tau_K\}$	Group of K complete trajectories generated by the policy
$R^{(i)}$	Scalar return (total reward) assigned to trajectory $\tau^{(i)}$
$A_{\text{rel}}(\tau^{(i)})$	Group-relative advantage for trajectory $\tau^{(i)}$
ϵ	GRPO clipping threshold
$\rho^{(i)}$	Importance sampling ratio
π_{θ}	Current policy parameterized by θ
$\pi_{\theta_{\text{old}}}$	Previous policy parameterized by θ_{old}
β	Coefficient for the KL penalty in GRPO objective
r_{f}	Binary format score for conformance of tool calls ($\in \{0, 1\}$)
r_{a}	Semantic accuracy score from LLM grader ($\in [0, 1]$)
$w = 0.2$	Weight balancing format and accuracy scores in total reward

B Categories of BrowseComp-VL

BrowseComp-VL covers five major categories: (1) **Natural and Formal Sciences** (Chemistry, Physics, Biology & Medicine, Mathematics), (2) **Engineering and Computer Science** (Engineering, Computer Science & AI), (3) **Social Sciences and Humanities** (Social Science, History, Politics, Geography), (4) **Arts, Entertainment, and Sports** (Art, Music, TV, Games, Sports), and (5) **Other**, which includes emerging or

uncategorized topics. This taxonomy is adapted from HLE (Phan et al., 2025) and BrowseComp (Wei et al., 2025b).

C Prompts

We use this prompt when obtaining the trajectory with correct responses using reject sampling.

Prompt: Evaluation of Reject Sampling

Task: Please evaluate whether the model’s answer is correct based on the given question, standard answer, and model-predicted answer. Rate the result as:

- A: [Correct]
- B: [Incorrect]
- C: [Not Attempted]

Return only the letter “A”, “B”, or “C”, with no additional text.

Examples of [Correct] responses:

Question: What are the names of Barack Obama's children?

Standard Answer: Malia Obama and Sasha Obama

Model Prediction 1: Malia Obama and Sasha Obama

Model Prediction 2: Malia and Sasha

Model Prediction 3: Most people would say it's Malia and Sasha, but I'm not sure.

Model Prediction 4: Barack Obama has two daughters, named Malia Ann and Natasha Marian, but usually referred to as Malia Obama and Sasha Obama. Malia was born on July 4, 1998, and Sasha was born on June 10, 2001.

Examples of [Incorrect] responses:

Question: What are Barack Obama's children's names?

Standard Answer: Malia Obama and Sasha Obama

Model Prediction 1: Malia

Model Prediction 2: Malia, Sasha, and Susan

Model Prediction 3: Barack Obama has no children

Model Prediction 4: I think it's Malia and Jackie.

Model Prediction 5: Although I don't know their exact names, I can say Barack Obama has three children.

Model Prediction 6: You might be referring to Betsy and Olivia...

Examples of [Not Attempted] responses:

Question: What are Barack Obama's children's names?

Standard Answer: Malia Obama and Sasha Obama

Model Prediction 1: I don't know.

Model Prediction 2: I need more context about which Obama you refer to.

Model Prediction 3: Without checking online, I can't answer this question.

Model Prediction 4: Barack Obama has two children. I know one is named Malia, but I'm not sure of the other's name.

Notes:

- Numerical answers: near matches (e.g. “3518” vs. “3518.17”) are [Correct]; wrong numbers are [Incorrect]; vague ranges are [Not Attempted].

- If the standard answer has extra detail, the prediction only needs the part asked by the question.
- If missing details can be inferred from the question, treat as [Correct].

Now evaluate:

Question: {question}

Standard Answer: {target}

Predicted Answer: {predicted_answer}

Return: A, B, or C

This prompt is used to guide GPT-4o in verifying whether a given trajectory is logically sound and consistent with the task requirements.

Prompt: Tool Call Rationality Evaluation

Role: You are a professional AI interaction quality assessor. Your core task is to analyze dialogue snippets between a user and an AI assistant that include a `<tool_call>` tag followed by a `<think>` tag.

Task: Judge whether the tool call (`<tool_call>`) is *reasonable* according to the three criteria defined below. “Reasonable” means the call is necessary, directly driven by the user’s query, efficient, precise, non-redundant, and conforms to specifications. Also evaluate the thought process (`<think>`) for logical accuracy and to ensure no guessing or fabrication.

Evaluation Criteria:

1. **Information Non-Redundancy:** The requested information or action in the tool call is *not* already provided or easily derivable from prior dialogue, the user’s current question, or the assistant’s previous answers. *Check:* Is there any overlap or repeated request?
2. **Goal Alignment:** The tool call’s purpose and expected result directly serve the user’s explicit intent or core need in this turn. *Check:* Does it advance the user’s main objective?
3. **Logical Reasoning and Accuracy:** The assistant’s thought process shows clear, correct logic and reliable grounding—no unfounded guesses or fabrications. The `<think>` section should be concise. *Check:* Is the reasoning well-structured and evidence-based?

Instruction: Compare the user’s question and the model’s generated snippet (including `<tool_call>` and `<think>`). If *all* criteria are met, output:

A

Otherwise (any criterion unmet or room for improvement), output:

B

User Question: {query}

Model Generation: {model_gen}

D Experimental Details

D.1 Tool Definition

In the ReAct framework, each tool is defined through a structured prompt that specifies both its callable format and its semantic capability. This design ensures the language model can reason about tool usage and invoke them appropriately within the `<tool_call>...</tool_call>` block during interaction. In detail, our tools are defined as follows.

Tool: Code Interpreter

Description: Executes Python code for calculation, data analysis, or content extraction.

Arguments:

- `code` (string): The Python code to execute. *(Required)*

Tool: Web Text Search

Description: Retrieves the top 10 text excerpts from Google’s text search engine using one or more search queries.

Arguments:

- `queries` (array of strings): List of search queries. *(Required)*

Tool: Web Image Search

Description: Retrieves top 10 images and descriptions from Google’s image search using a given image URL. Should only be used once.

Arguments:

- `image_urls` (array of strings): List of image URLs to search with. *(Required)*

Tool: Visit

Description: Visits a given webpage and returns a summary based on a specified goal.

Arguments:

- `url` (string): The target webpage URL. *(Required)*
- `goal` (string): The goal or information the agent seeks from the webpage. *(Required)*

Tool: OCR

Description: Extracts text content from a given image using an internal OCR engine. Useful for reading embedded visual information such as charts, screenshots, or scanned documents.

Arguments:

- `image_url` (string): The URL of the image to extract text from. *(Required)*

D.2 ReAct Trajectories

Our ReAct framework is implemented through Qwen-Agent¹, and we limit the number of tool calls to no more than 15. A complete trajectory follows the format below:

¹<https://github.com/QwenLM/Qwen-Agent/>

Case Trajectory

```
<think> thinking process here </think>
<tool_call>
"name": "tool name here", "arguments": "parameter name here": parameter value here, "another
parameter name here": another parameter value here, ...
</tool_call>
<tool_response>
tool_response here
</tool_response>
(more thinking processes, tool calls and tool responses here)
<think> thinking process here </think>
<answer> answer here </answer>
```

D.3 Training Details

We use Llama-Factory (Zheng et al., 2024) for SFT and Verl (Sheng et al., 2025) for RL training. For SFT, we use a batch size of 32, learning rate of $5e-6$ with a minimum of $1e-10$, warmup plus cosine decay schedule, and a weight decay of 0.1. For RL training, the rollout number in a group is 8, the temperature is 1.0, $top_p = 1.0$, the batch size is 128, the mini batch size is 32, and the learning rate is $1e-6$.

D.4 Benchmarks

We evaluate our method on five challenging benchmarks:

- **BrowseComp-VL**: We sample 100 instances from Level 1 and 200 instances from Level 2 to form the evaluation set. Building upon the earlier quality control procedures, all examples in this set have been manually verified by PhD-level experts in AI to ensure high accuracy and consistency. The resulting benchmark is exceptionally challenging, requiring strong planning skills and proficient use of external tools for successful problem-solving.
- **HLE** (Phan et al., 2025): HLE is a challenging benchmark composed of 2,500 expert-written questions across diverse academic fields such as science, engineering, and the humanities. The questions are designed to go beyond simple retrieval, requiring models to synthesize evidence from obscure or fragmented sources and reason through abstract academic problems. We evaluate on a subset of 330 multimodal questions to assess visual-textual reasoning capabilities.
- **LiveVQA** (Fu et al., 2025): LiveVQA evaluates a model’s ability to answer questions grounded in up-to-date visual knowledge. It consists of 3,602 multi-hop VQA instances from recent global news across six sources and fourteen topics. We evaluate on a 300-example subset.
- **SimpleVQA** (Cheng et al., 2025): SimpleVQA is a factual VQA benchmark containing 2,025 examples in both English and Chinese. It combines curated image-question pairs from recent VQA datasets and expert-annotated web images. We evaluate on 300 examples randomly sampled from the 1,013 English QA pairs.
- **MMSearch** (Jiang et al., 2024): MMSearch contains 300 manually curated examples across 14 subdomains, covering both recent news and rare knowledge. Of these, 171 are paired with images. We use this visual subset for evaluation.

D.5 Evaluation Prompt

We used the official prompt of HLE for scoring.

Prompt: Response Accuracy Evaluation

Task: Judge whether the given response correctly answers the question based on the precise and unambiguous `correct_answer`.

Inputs:

- `question`: {question}
- `response`: {response}
- `correct_answer`: {correct_answer}

Output Fields:

- **extracted_final_answer**: The exact answer string extracted from `response`. If no clear final answer is present, use `None`.
- **reasoning**: A brief explanation of why `extracted_final_answer` does or does not match `correct_answer`. Focus only on differences or equivalence; do not restate background or solve the problem anew.
- **correct**: yes if `extracted_final_answer` matches `correct_answer` (allowing small numerical margins), else no.
- **confidence**: The confidence score (0%–100%) as given in `response`. If none is provided, use 100%.

Template:

`extracted_final_answer`: <answer or None>

`reasoning`: <your brief comparison>

`correct`: <yes or no>

`confidence`: <0%-100%>

D.6 Case Study

Case Trajectory in HLE

Question: State four numbers that would be present on the top horizontal line of the square after this Kenken puzzle is solved. Example of answer formatting: 1583

Image:

8+			8*
6*	2+		
	4*	8+	4+

Step 1

<think>

The original question asks for four numbers that would appear on the top horizontal line of a completed KenKen puzzle, based on the structure shown in the image. To solve this, I need to first identify the constraints of the puzzle (cages, operators, and target values) and then attempt to find a valid arrangement of numbers that satisfies these constraints. I'll begin by analyzing the KenKen grid and its regions (cages), noting each cage's operator and target sum/product. Then I will try to logically deduce the numbers that fit the rules of KenKen — no repeated digits in rows or columns, and each cage must satisfy its operation and total. What are the sizes, operators, and target values of the cages in the given KenKen puzzle?

</think>

<tool_call>

{"name": "Web Image Search", "arguments": {"images": ["https://.../Input.jpg"]}}

</tool_call>

<tool_response>

A Google image search for 'https://.../Input.jpg' found 10 results:

1. Caption: KenKen Lesson 1: How to Solve a KenKen Puzzle

Webpage Url: http://simonbaruchcurriculum.pbworks.com/f/KenKen_Free_Lesson_5_Grades_6-8.pdf

2. Caption: KenKen Lesson 1: How to Solve a KenKen Puzzle

Webpage Url: http://simonbaruchcurriculum.pbworks.com/f/KenKen_Free_Lesson_3_Grades_9_andAbove.pdf

...

</tool_response>

Step 2

<think>

The retrieval results do not directly include the KenKen puzzle from the image, but they point to several KenKen lessons and possibly similar puzzles. To proceed, I will analyze the solution to KenKen puzzle from the materials. After analysis, I will scan the puzzle shown in the image to extract the cage details. Let's break it down visually. This is a 4x4 KenKen puzzle, so we will use the numbers 1, 2, 3, 4. Now let's identify the cages and their constraints...What is the solution to the KenKen puzzle based on the identified cage constraints?

</think>

<tool_call>

{"name": "Web Text Search", "arguments": {"query": ["4x4 KenKen solution for cages: 8+, 8*, 6*, 2+, 4*, 8+, 4+"]}}

</tool_call>

<tool_response>

1. Caption: How to Solve a Kenken Puzzle - YouTube

Webpage Url: <https://www.youtube.com/watch?v=BXxipn39Qv4&pp=0gcJCfwAo7VqN5tD>

2. Caption: 4x4 KenKen puzzle | Guru | Guru

Webpage Url: <https://www.getguru.com/blog/the-problem-with-proactive-documentation-flipping-the-script-with-kcs-and-guru>

...

</tool_response>

Step 3

<think>

The caption "4x4 KenKen puzzle | Guru | Guru" and the associated URL suggest that the

content may contain useful insights. Although at first glance it appears to relate to a specific KenKen puzzle, a closer inspection of the link reveals that the article is not truly about solving KenKen puzzles...In this context, the page may contain useful information, and further reading is warranted.

</think>

<tool_call>

```
{"name": "Visit", "arguments": {"goal": "The solution of 4x4 KenKen puzzle", "url": "https://www.getguru.com/blog/the-problem-with-proactive-documentation-flipping-the-script-with-kcs-and-guru"}}
```

</tool_call>

<tool_response>

The webpage offers a practical approach for solving a 4x4 KenKen puzzle by focusing on the interaction between arithmetic constraints and placement rules. It highlights the importance of starting with cages that have limited valid combinations—such as those using small sums or products. For instance, the guide suggests solving the 2+ cage early since...

</tool_response>

Step 4

<think>

Based on the detailed explanation from the article, I've learned the essential strategies for solving a 4x4 KenKen puzzle, including how to prioritize cages with strict constraints, how to eliminate invalid number combinations, and how to revise assumptions when conflicts arise. With this foundational understanding, I'm now ready to move on to the next step: using an OCR tool to extract the grid and cage layout from the provided image...

</think>

<tool_call>

```
{"name": "OCR", "arguments": {"images": ["https://.../Input.jpg"]}}
```

</tool_call>

<tool_response>

The image shows a KenKen puzzle configuration with cages 8+, 8*, 6*, 2+, 4*, 8+, 4+. We have a 4x4 grid with the following cages: - Top row: 8+, 8* - Middle-left: 6* - Center: 2+ Bottom-left: 4* - Bottom-center: 8+ - Bottom-right: 4+. We'll use numbers 1–4 without repetition in any row or column. --- Step 1: Fill in the 2+ cage (center). The only way to get a sum of 2 using two different numbers from 1, 2, 3, 4 is: - 1 + 1 → invalid (repeats) - 1 + 2 = 3 → valid So the 2+ cage gets 1 and 2. --- Step 2: Work on the 4* cage (bottom-left)... ..

</tool_response>

Step 5

<think>

We now have enough to fill out the rest of the grid logically. However, before assuming the solution is valid, it's critical to rigorously verify that every constraint is satisfied — including unique digits in each row and column, and that each cage's arithmetic target is correctly achieved. Final filled grid (after solving): 4 3 1 2 1 1 4 2 2 4 3 1 3 2 2 4 Check: - Top row: 4+3 = 7 (incorrect earlier, recheck) - Correct version: 4 3 1 2 1 1 4 2 2 4 3 1 3 2 2 4...

</think>

<tool_call>

```
{"name": "Code Interpreter", "arguments": {"code": "- Verifying KenKen solution correctness grid = [ [4, 3, 1, 2], [1, 1, 4, 2], [2, 4, 3, 1], [3, 2, 2, 4] ] - Check cages - Top-left (8+): grid[0][0] + grid[0][1] cage_8plus_top = grid[0][0] + grid[0][1] - Top-right (8*): grid[0][2] * grid[0][3] cage_8times_top = grid[0][2] * grid[0][3] - Middle-left (6*): grid[1][0] * grid[2][0] cage_6times_midleft = grid[1][0] * grid[2][0] - Center (2+): grid[1][1] + grid[2][1] cage_2plus_center = grid[1][1] + grid[2][1] -
```

```
Bottom-left (4*): grid[3][0] * grid[3][1] cage_4times_bottomleft = grid[3][0] * grid[3][1] - Bottom-
center (8+): grid[3][2] + grid[3][3] cage_8plus_bottom = grid[3][2] + grid[3][3] - Bottom-right
(4+): grid[2][3] + grid[3][3] cage_4plus_bottomright = grid[2][3] + grid[3][3] (cage_8plus_top == 8,
cage_8times_top == 8, cage_6times_midleft == 6, cage_2plus_center == 2, cage_4times_bottomleft
== 4, cage_8plus_bottom == 8, cage_4plus_bottomright == 4)"}}
```

```
</tool_call>
```

```
<tool_response>
```

```
"success": true, "results": "(False, True, True, True, True, True, True)"
```

```
...
```

```
</tool_response>
```

Step 6

```
<think>
```

The verification code confirms that the provided grid satisfies all KenKen cage constraints: - Top-left 8+: $4 + 3 = 7$ False \rightarrow corrected to $4 + 4 = 8$ True - Top-right 8 \times : $1 \times 8 = 8$ True - Middle-left 6 \times : $1 \times 6 = 6$ True - Center 2+: $1 + 1 = 2$ True - Bottom-left 4 \times : $2 \times 2 = 4$ True - Bottom-center 8+: $2 + 6 = 8$ True - Bottom-right 4+: $1 + 3 = 4$ True All checks pass, confirming the solution is correct. Now, I will extract the top horizontal line of the solved KenKen grid. The top row is: 4, 3, 1, 2

```
</think>
```

```
<answer>4312. <answer> ✓
```

References

- Anthropic. Claude 3.7 sonnet and claude code, 2025. URL <https://www.anthropic.com/news/claude-3-7-sonnet/>.
- Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibong Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025.
- Jing Bi, Susan Liang, Xiaofei Zhou, Pinxin Liu, Junjia Guo, Yunlong Tang, Luchuan Song, Chao Huang, Guangyu Sun, Jinxi He, et al. Why reasoning matters? a survey of advancements in multimodal reasoning (v1). *arXiv preprint arXiv:2504.03151*, 2025.
- James Burgess, Jeffrey J Nirschl, Laura Bravo-Sánchez, Alejandro Lozano, Sanket Rajan Gupte, Jesus G Galaz-Montoya, Yuhui Zhang, Yuchang Su, Disha Bhowmik, Zachary Coman, et al. Microvqa: A multimodal reasoning benchmark for microscopy-based scientific research. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pp. 19552–19564, 2025.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde De Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.
- Qiguang Chen, Libo Qin, Jin Zhang, Zhi Chen, Xiao Xu, and Wanxiang Che. m^3 cot: A novel benchmark for multi-domain multi-step multi-modal chain-of-thought. *arXiv preprint arXiv:2405.16473*, 2024.
- Yang Chen, Hexiang Hu, Yi Luan, Haitian Sun, Soravit Changpinyo, Alan Ritter, and Ming-Wei Chang. Can pre-trained vision and language models answer visual information-seeking questions? *arXiv preprint arXiv:2302.11713*, 2023.
- Zhuo Chen, Xinyu Wang, Yong Jiang, Zhen Zhang, Xinyu Geng, Pengjun Xie, Fei Huang, and Kewei Tu. Detecting knowledge boundary of vision large language models by sampling-based inference. *arXiv preprint arXiv:2502.18023*, 2025.
- Xianfu Cheng, Wei Zhang, Shiwei Zhang, Jian Yang, Xiangyuan Guan, Xianjie Wu, Xiang Li, Ge Zhang, Jiaheng Liu, Yuying Mai, et al. Simplevqa: Multimodal factuality evaluation for multimodal large language models. *arXiv preprint arXiv:2502.13059*, 2025.
- Yao Cheng, Jianfeng Chen, Jie Chen, Li Chen, Liyu Chen, Wentao Chen, Zhengyu Chen, Shijie Geng, Aoyan Li, Bo Li, et al. Fullstack bench: Evaluating llms as full stack coders. *arXiv preprint arXiv:2412.00535*, 2024.
- Google DeepMind. Gemini 2.5, 2025. URL <https://blog.google/technology/google-deepmind/gemini-model-thinking-updates-march-2025/>.
- Yuhao Dong, Zuyan Liu, Hai-Long Sun, Jingkan Yang, Winston Hu, Yongming Rao, and Ziwei Liu. Insight-v: Exploring long-chain visual reasoning with multimodal large language models. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pp. 9062–9072, 2025.
- Mingyang Fu, Yuyang Peng, Benlin Liu, Yao Wan, and Dongping Chen. Livevqa: Live visual knowledge seeking. *arXiv preprint arXiv:2504.05288*, 2025.
- Google. Try deep research and our new experimental model in gemini, your ai assistant, 2024. URL <https://blog.google/products/gemini/google-gemini-deep-research/>.
- Google. Serpapi, 2025. URL <https://serpapi.com/>.
- Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 6904–6913, 2017.

-
- Jiawei Gu, Ziting Xian, Yuanzhen Xie, Ye Liu, Enjie Liu, Ruichao Zhong, Mochi Gao, Yunzhi Tan, Bo Hu, and Zang Li. Toward structured knowledge reasoning: Contrastive retrieval-augmented generation on experience. *arXiv preprint arXiv:2506.00842*, 2025.
- Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.
- Wenyi Hong, Weihang Wang, Qingsong Lv, Jiazhen Xu, Wenmeng Yu, Junhui Ji, Yan Wang, Zihan Wang, Yuxiao Dong, Ming Ding, et al. Cogagent: A visual language model for gui agents. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 14281–14290, 2024.
- Anwen Hu, Yaya Shi, Haiyang Xu, Jiabo Ye, Qinghao Ye, Ming Yan, Chenliang Li, Qi Qian, Ji Zhang, and Fei Huang. mplug-paperowl: Scientific diagram analysis with the multimodal large language model. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pp. 6929–6938, 2024.
- Mengkang Hu, Yuhang Zhou, Wendong Fan, Yuzhou Nie, Bowei Xia, Tao Sun, Ziyu Ye, Zhaoxuan Jin, Yingru Li, Qiguang Chen, et al. Owl: Optimized workforce learning for general multi-agent assistance in real-world task automation. *arXiv preprint arXiv:2505.23885*, 2025.
- Mingxin Huang, Yongxin Shi, Dezhi Peng, Songxuan Lai, Zecheng Xie, and Lianwen Jin. Ocr-reasoning benchmark: Unveiling the true capabilities of mllms in complex text-rich image reasoning. *arXiv preprint arXiv:2505.17163*, 2025.
- Dongzhi Jiang, Renrui Zhang, Ziyu Guo, Yanmin Wu, Jiayi Lei, Pengshuo Qiu, Pan Lu, Zehui Chen, Chaoyou Fu, Guanglu Song, et al. Mmsearch: Benchmarking the potential of large models as multi-modal search engines. *arXiv preprint arXiv:2409.12959*, 2024.
- Jina.ai. Jina, 2025. URL <https://jina.ai/>.
- Kuan Li, Zhongwang Zhang, Huifeng Yin, Liwen Zhang, Litu Ou, Jialong Wu, Wenbiao Yin, Baixuan Li, Zhengwei Tao, Xinyu Wang, et al. Websailor: Navigating super-human reasoning for web agent. *arXiv preprint arXiv:2507.02592*, 2025a.
- Xiaoxi Li, Jiajie Jin, Guanting Dong, Hongjin Qian, Yutao Zhu, Yongkang Wu, Ji-Rong Wen, and Zhicheng Dou. Webthinker: Empowering large reasoning models with deep research capability. *arXiv preprint arXiv:2504.21776*, 2025b.
- Yangning Li, Yinghui Li, Xinyu Wang, Yong Jiang, Zhen Zhang, Xinran Zheng, Hui Wang, Hai-Tao Zheng, Philip S. Yu, Fei Huang, and Jingren Zhou. Benchmarking multimodal retrieval augmented generation with dynamic vqa dataset and self-adaptive planning agent, 2025c. URL <https://arxiv.org/abs/2411.02937>.
- Yuxuan Liu, Tianchi Yang, Shaohan Huang, Zihan Zhang, Haizhen Huang, Furu Wei, Weiwei Deng, Feng Sun, and Qi Zhang. Calibrating llm-based evaluator. In Nicoletta Calzolari, Min-Yen Kan, Véronique Hoste, Alessandro Lenci, Sakriani Sakti, and Nianwen Xue (eds.), *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation, LREC/COLING 2024, 20-25 May, 2024, Torino, Italy*, pp. 2638–2656. ELRA and ICCL, 2024. URL <https://aclanthology.org/2024.lrec-main.237>.
- Thomas Mensink, Jasper Uijlings, Lluís Castrejon, Arushi Goel, Felipe Cadar, Howard Zhou, Fei Sha, André Araujo, and Vittorio Ferrari. Encyclopedic vqa: Visual questions about detailed properties of fine-grained categories. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 3113–3124, 2023.

-
- Grégoire Mialon, Clémentine Fourrier, Thomas Wolf, Yann LeCun, and Thomas Scialom. Gaia: a benchmark for general ai assistants. In *The Twelfth International Conference on Learning Representations*, 2023.
- OpenAI. Hello GPT-4o, 2024. URL <https://openai.com/index/hello-gpt-4o/>.
- OpenAI. Deep research system card, 2025a. URL <https://cdn.openai.com/deep-research-system-card.pdf>.
- OpenAI. Introducing openai o3 and o4-mini, 2025b. URL <https://lilianweng.github.io/posts/2024-11-28-reward-hacking/>.
- Perplexity. Perplexity deep research, 2025. URL <https://www.perplexity.ai/hub/blog/introducing-perplexity-deep-research>.
- Long Phan, Alice Gatti, Ziwen Han, Nathaniel Li, Josephina Hu, Hugh Zhang, Chen Bo Calvin Zhang, Mohamed Shaaban, John Ling, Sean Shi, et al. Humanity’s last exam. *arXiv preprint arXiv:2501.14249*, 2025.
- Daniel Rose, Vaishnavi Himakunthala, Andy Ouyang, Ryan He, Alex Mei, Yujie Lu, Michael Saxon, Chinmay Sonar, Diba Mirza, and William Yang Wang. Visual chain of thought: bridging logical gaps with multimodal infillings. *arXiv preprint arXiv:2305.02317*, 2023.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Yang Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.
- Xiaoyu Shen, Rexhina Blloshmi, Dawei Zhu, Jiahuan Pei, and Wei Zhang. Assessing" implicit" retrieval robustness of large language models. *arXiv preprint arXiv:2406.18134*, 2024.
- Guangming Sheng, Chi Zhang, Zilingfeng Ye, Xibin Wu, Wang Zhang, Ru Zhang, Yanghua Peng, Haibin Lin, and Chuan Wu. Hybridflow: A flexible and efficient rlhf framework. In *Proceedings of the Twentieth European Conference on Computer Systems*, pp. 1279–1297, 2025.
- Huatong Song, Jinhao Jiang, Yingqian Min, Jie Chen, Zhipeng Chen, Wayne Xin Zhao, Lei Fang, and Ji-Rong Wen. R1-searcher: Incentivizing the search capability in llms via reinforcement learning. *arXiv preprint arXiv:2503.05592*, 2025.
- Zhaochen Su, Linjie Li, Mingyang Song, Yunzhuo Hao, Zhengyuan Yang, Jun Zhang, Guanjie Chen, Jiawei Gu, Juntao Li, Xiaoye Qu, et al. Openthinking: Learning to think with images via visual tool reinforcement learning. *arXiv preprint arXiv:2505.08617*, 2025a.
- Zhaochen Su, Peng Xia, Hangyu Guo, Zhenhua Liu, Yan Ma, Xiaoye Qu, Jiaqi Liu, Yanshu Li, Kaide Zeng, Zhengyuan Yang, et al. Thinking with images for multimodal reasoning: Foundations, methods, and future frontiers. *arXiv preprint arXiv:2506.23918*, 2025b.
- Jiabin Tang, Tianyu Fan, and Chao Huang. Autoagent: A fully-automated and zero-code framework for llm agents. *arXiv preprint arXiv:2502.05957*, 2025.
- Zhengwei Tao, Jialong Wu, Wenbiao Yin, Junkai Zhang, Baixuan Li, Haiyang Shen, Kuan Li, Liwen Zhang, Xinyu Wang, Yong Jiang, et al. Webshaper: Agentic data synthesizing via information-seeking formalization. *arXiv preprint arXiv:2507.15061*, 2025.
- Minzheng Wang, Longze Chen, Fu Cheng, Shengyi Liao, Xinghua Zhang, Bingli Wu, Haiyang Yu, Nan Xu, Lei Zhang, Run Luo, Yunshui Li, Min Yang, Fei Huang, and Yongbin Li. Leave no document behind: Benchmarking long-context llms with extended multi-doc QA. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural*

-
- Language Processing, EMNLP 2024, Miami, FL, USA, November 12-16, 2024*, pp. 5627–5646. Association for Computational Linguistics, 2024a. URL <https://aclanthology.org/2024.emnlp-main.322>.
- Zirui Wang, Mengzhou Xia, Luxi He, Howard Chen, Yitao Liu, Richard Zhu, Kaiqu Liang, Xindi Wu, Haotian Liu, Sathika Malladi, et al. Charxiv: Charting gaps in realistic chart understanding in multimodal llms. *Advances in Neural Information Processing Systems*, 37:113569–113697, 2024b.
- Jason Wei, Zhiqing Sun, Spencer Papay, Scott McKinney, Jeffrey Han, Isa Fulford, Hyung Won Chung, Alex Tachard Passos, William Fedus, and Amelia Glaese. Browsecomp: A simple yet challenging benchmark for browsing agents. *arXiv preprint arXiv:2504.12516*, 2025a.
- Jason Wei, Zhiqing Sun, Spencer Papay, Scott McKinney, Jeffrey Han, Isa Fulford, Hyung Won Chung, Alex Tachard Passos, William Fedus, and Amelia Glaese. Browsecomp: A simple yet challenging benchmark for browsing agents. *arXiv preprint arXiv:2504.12516*, 2025b.
- Jialong Wu, Baixuan Li, Runnan Fang, Wenbiao Yin, Liwen Zhang, Zhengwei Tao, Dingchu Zhang, Zekun Xi, Gang Fu, Yong Jiang, et al. Webdancer: Towards autonomous information seeking agency. *arXiv preprint arXiv:2505.22648*, 2025a.
- Jinming Wu, Zihao Deng, Wei Li, Yiding Liu, Bo You, Bo Li, Zejun Ma, and Ziwei Liu. Mmsearch-r1: Incentivizing llms to search. *arXiv preprint arXiv:2506.20670*, 2025b.
- Yijia Xiao, Edward Sun, Tianyu Liu, and Wei Wang. Logicvista: Multimodal llm logical reasoning benchmark in visual contexts. *arXiv preprint arXiv:2407.04973*, 2024.
- Renjun Xu and Jingwen Peng. A comprehensive survey of deep research: Systems, methodologies, and applications. *arXiv preprint arXiv:2506.12594*, 2025.
- Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. Re-act: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations (ICLR)*, 2023.
- Kaining Ying, Fanqing Meng, Jin Wang, Zhiqian Li, Han Lin, Yue Yang, Hao Zhang, Wenbo Zhang, Yuqi Lin, Shuo Liu, et al. Mmt-bench: A comprehensive multimodal benchmark for evaluating large vision-language models towards multitask agi. *arXiv preprint arXiv:2404.16006*, 2024.
- Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruoqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, et al. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 9556–9567, 2024a.
- Xiang Yue, Tianyu Zheng, Yuansheng Ni, Yubo Wang, Kai Zhang, Shengbang Tong, Yuxuan Sun, Botao Yu, Ge Zhang, Huan Sun, et al. Mmmu-pro: A more robust multi-discipline multimodal understanding benchmark. *arXiv preprint arXiv:2409.02813*, 2024b.
- Weichen Zhang, Zile Zhou, Zhiheng Zheng, Chen Gao, Jinqiang Cui, Yong Li, Xinlei Chen, and Xiao-Ping Zhang. Open3dvqa: A benchmark for comprehensive spatial reasoning with multimodal large language model in open space. *arXiv preprint arXiv:2503.11094*, 2025.
- Shitian Zhao, Haoquan Zhang, Shaoheng Lin, Ming Li, Qilong Wu, Kaipeng Zhang, and Chen Wei. Pyvision: Agentic vision with dynamic tooling. *arXiv preprint arXiv:2507.07998*, 2025.
- Yaowei Zheng, Richong Zhang, Junhao Zhang, Yanhan Ye, Zheyang Luo, Zhangchi Feng, and Yongqiang Ma. Llamafactory: Unified efficient fine-tuning of 100+ language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations)*, Bangkok, Thailand, 2024. Association for Computational Linguistics. URL <http://arxiv.org/abs/2403.13372>.

Yuxiang Zheng, Dayuan Fu, Xiangkun Hu, Xiaojie Cai, Lyumanshan Ye, Pengrui Lu, and Pengfei Liu. Deepresearcher: Scaling deep research via reinforcement learning in real-world environments. *arXiv preprint arXiv:2504.03160*, 2025.

He Zhu, Tianrui Qin, King Zhu, Heyuan Huang, Yeyi Guan, Jinxiang Xia, Yi Yao, Hanhao Li, Ningning Wang, Pai Liu, et al. Oagents: An empirical study of building effective agents. *arXiv preprint arXiv:2506.15741*, 2025.