Fathom-Search-4B: Scaling DeepSearch Reasoning Capabilities via RL

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Abstract

We present Fathom-Search-4B, a 4B-parameter, tool-using LLM trained to perform evidence-based DeepSearch over heterogeneous sources (HTML, PDFs, blogs). Our approach combines three advances. First, DUETQA, a 5K example dataset generated via multi-agent self-play, enforces live-web dependence, post-2024 recency, and diversity beyond Wikipedia. Second, we introduce RAPO, a zero-overhead extension of GRPO that stabilizes multi-turn RL via prompt-level pruning of saturated items, reward-aware advantage scaling to preserve gradient magnitude, and a per-prompt replay buffer that restores variance. Third, we design a steerable step-level reward that labels each tool call as exploration, verification, or redundant, allowing explicit control over search breadth, cross-source verification depth, and overall tool-use horizon; this reliably extends effective trajectories beyond 10+ tool calls when warranted. The agent operates with a goal-conditioned retrieval stack (search selection + targeted page querying), improving signal-to-noise versus snippet-only or greedy retrieval. Evaluated on DeepSearch benchmarks (e.g., SimpleQA, FRAMES, WebWalker, Seal0, MuSiQue) and out-of-domain reasoning suites (HLE, AIME-25, GPQA-Diamond, MedQA), Fathom-Search-4B attains state-of-the-art results among open models, with large gains on retrieval-heavy tasks and strong transfer to STEM/medical QA.

https://github.com/FractalAIResearchLabs/Fathom-DeepResearch

1 Introduction

Large Language Models (LLMs) have demonstrated promising results across a diverse set of tasks, such as mathematical reasoning, code generation [9, 5, 24, 23]. Despite these advancements, they remain prone to factual inaccuracies/hallucinations as they rely on static internal knowledge acquired during pretraining. Real world information is continually evolving and getting updated. Given the high cost of pretraining LLMs, it is not pragmatic to rely solely on repeated pretraining to update their knowledge. A potential solution to this problem involves enabling LLMs to interface with external knowledge systems.

Retrieval-augmented generation (RAG) has become the standard framework for open-domain QA, where LLMs generate answers conditioned on retrieved context. However, these pipelines rely on

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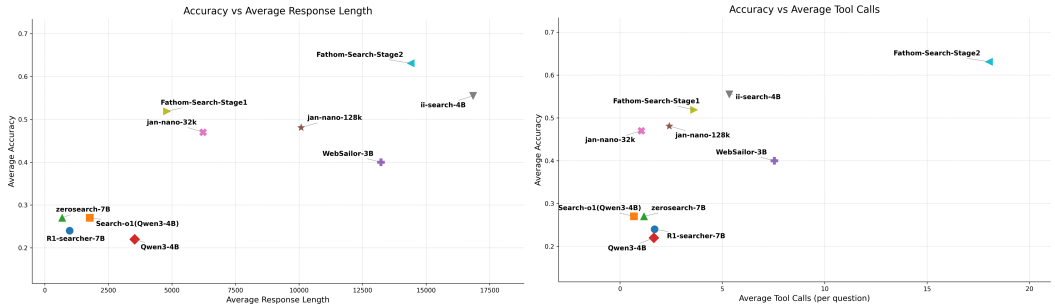

Figure 1: Accuracy vs Response length and Accuracy vs Number of Tool calls plot, demonstrating the long horizon tool interaction ability of Fathom-Search-4B, compared to its contemporaries.

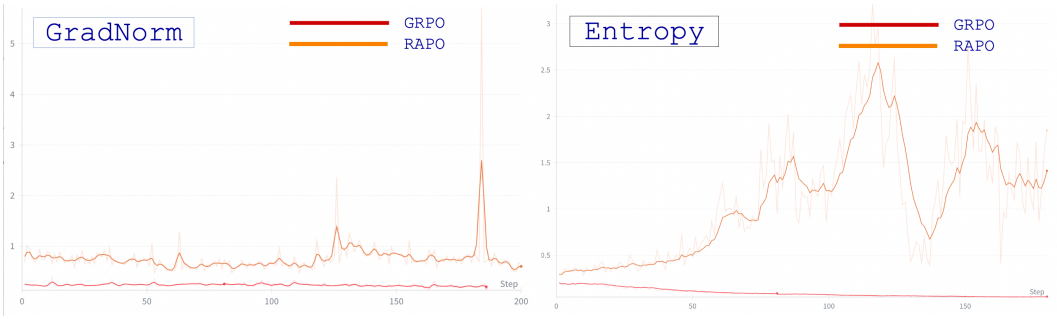

Figure 2: Comparison of policy entropy and gradient norm during RLVR training. GRPO exhibits rapid entropy collapse and diminished gradient norms due to sparse rewards, whereas RAPO sustains exploration and stronger updates via targeted updates

structured, static corpora and predictable input formats conditions rarely met in real-world search tasks. In contrast, recent efforts [26, 13, 25] have focused on instilling tool-mediated DeepSearch reasoning capabilities in LLMs that involve free-form web queries, parsing heterogeneous/noisy outputs, and synthesizing multi-step reasoning chains. The core principle underlying this approach is to concentrate training efforts on developing the model's ability to autonomously and effectively access and leverage external information sources (search engines). Rather than directly incorporating factual content into the model parameters, this method emphasizes teaching the model how to navigate, comprehend, and utilize relevant information from vast digital information landscapes for complex-information seeking tasks. This distinction makes DeepSearch fundamentally more difficult than traditional RAG and a necessary precursor to the next scaling milestone in search augmented language model capabilities: *DeepResearch Agents*

However, scaling DeepSearch capability faces three key challenges: (i) the lack of high-quality, verifiable, scalable training dataset creation pipeline , (ii) algorithmic instability in multi-turn reinforcement learning (RL) with tools , and (iii) lazy tool calling behavior which hinders scaling deep information exploration and retrieval capabilities

1.1 Motivation

(1) Training instability of GRPO in multi-turn tool interaction: RLVR (Reinforcement Learning with verifiable rewards) algorithms such as GRPO [22] have demonstrated early promise in aligning LLMs with sparse reward signals for single-turn reasoning tasks, particularly in structured domains like Math/STEM [22, 34]. However, it struggles to scale to multi-turn tool-augmented environments. External tool interaction response induces distribution shift from the models set token generation patterns this leads to decoding instability and malformed generations that further accelerate entropy collapse [32]. Sparse rewards lead to group saturation and degenerate advantage normalization, while synchronous pipelines amplify stragglers and tie optimization progress to system latency. The non-stationary reward landscape of the live web further introduces oscillatory gradients that interact poorly with trajectory-only credit assignment and KL regularization.

(2) RLVR training fails to scale multi-turn tool interaction beyond 5-6 turns : *(a) Correctness-only sparse rewards do not scale to long-horizon tool calling* With a single end-of-episode correctness signal, training shows early gains (format adherence, basic tool calling competence) followed by rapid entropy collapse 2; the policy converges to short, myopic traces of roughly 5/6 tool calls irrespective of task difficulty due to sparse, delayed credit assignment and the lack of step-level signals for rewarding useful intermediate behaviors in incorrect trajectories. *(b) RL amplifies SFT priors, limiting control over the cognitive behaviors of the policy* [7]: Tool-use RL typically relies on an SFT cold start to elicit basic tool competence [13]; [6] RL then amplifies pre-existing cognitive behaviors seeded by SFT [7]. Standard RLVR affords limited control over exploration and verification strategy, so cold-start trajectory quality disproportionately shapes downstream behavior and restricts deeper, more economical search.

(3) Limited training data characterized by high and hard-to-reduce intrinsic information uncertainty:

Training datasets such as TriviaQA [11], and multi-hop variants like 2WIKI[8], and HotpotQA [35] represent problems where solutions can often be found through minimal set queries or even from a model's parametric knowledge alone. These datasets do not expose models to the real-world retrieval challenges posed by noisy, heterogeneous data sources like, PDFs, Online forums ,Youtube etc. Recent synthetic efforts [26, 13, 27] attempt to bridge this gap by simulating realistic search behavior. For instance, WebSailor's[13] SailorFog-QA constructs ambiguous queries using obfuscated subgraphs of entity graphs, while SimpleDeepResearcher [27] issues multi-stage search-summarize-generate tool calls over raw HTML. Despite their innovation, these pipelines remain expensive, brittle, and time-consuming. They rely on handcrafted heuristics, graph expansion, or multi-stage LLM orchestration, limiting scalability, topical diversity, and adaptability to new domains.

1.2 Our Contributions

To this end, we introduce a post-training recipe to create state-of-the-art DeepSearch enabled reasoning model, Fathom-Search-4B. We enlist our key contributions below:

- **Multi-agent self-play dataset.** We build DUETQA, a 5K-example dataset created through multi-agent self-play, designed to require *live web search* to answer its queries.
- **Two-stage RL-zero training.** We introduce a two-stage RL-Zero training framework that provides coarse control over the exploration and verification strategies developed by the model.
- **RAPO (GRPO extension).** We propose RAPO, a zero-overhead modification of GRPO that stabilizes multi-turn RL through dataset pruning, advantage scaling, and replay buffers. 1
- **Steerable step-level reward.** We design a novel step level reward that enables fine-grained control over long-horizon tool use, which scales tool use beyond $20+$ calls

2 Methodology

We describe the methodology underlying *Fathom-Search*, a tool-using LLM that leverages live web-search capabilities to do evidence based reasoning in a multi-turn tool interaction setting, achieving long-horizon tool use (>20 calls) when warranted. These capabilities arise from a combined approach of: (i) a curated synthetic data pipeline tailored to search-tool augmented reasoning, (ii) targeted upgrades to GRPO to effectively adapt it to multi-turn tool interaction, and (iii) a two-stage training regimen with reward shaping to expand the tool-use horizon in a steerable manner.

2.1 DuetQA: A synthetic Deep-search dataset, generated via multi-agent self play

To address the aforementioned challenges in Section 1., we develop a self-supervised dataset construction framework designed to yield verifiable, search-dependent, multi-hop QA pairs. This pipeline serves as the basis for generating DUETQA, a dataset tailored for training agentic deepsearch models. The design goals are: **Live web-search dependency**: for each QA pair (q, a), the question is unanswerable without search by enforcing that at least one hop contains information post–2024-01-01 (i.e., for a model $\mathcal{M}$, $P(a \mid q, \mathcal{M}_{\text{no-search}}) \ll P(a \mid q, \mathcal{M}_{\text{search}})$); **Diverse source domains**: questions

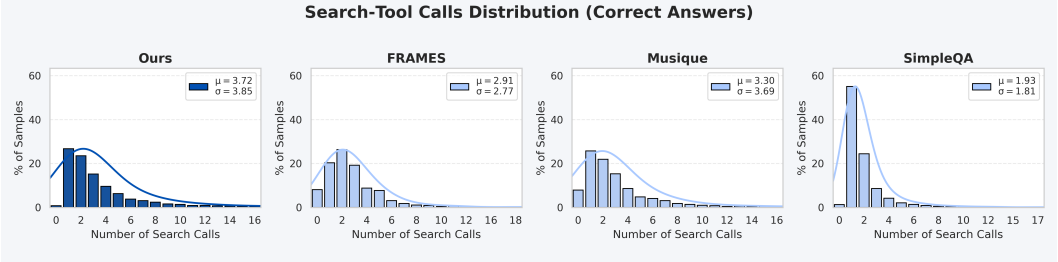

Figure 3: Distribution of search-call counts issued by o3 over correctly answered questions per benchmark, comparing DuetQA with other prominent benchmarks. DuetQA shows strict live-web-search dependence: o3[17] solves close to 0 questions DuetQA items without issuing a search call.

require querying beyond Wikipedia (e.g., online PDFs, news outlets, government filings, academic blogs, discussion forums); and **Steerable theme control**: each example is grounded in $k \in [5, 7]$ sampled themes $\mathcal{T}_{\text{sample}} \subset \mathcal{T}$, where $\mathcal{T}$ is a manually curated taxonomy of 200+ themes covering a broad range of topics. We generate questions using two frontier web search enabled LRMs, $\mathcal{M}_1$ (O3) and $\mathcal{M}_2$ (O4-mini) [17], acting as *proxy web-crawling agents* that produce QA pairs and as *independent verifiers* to that ensure question solvability; a third model, $\mathcal{M}_3$ (GPT-4o), is a *non-search* model used for controlled paraphrasing/obfuscation of questions and as a baseline verifier without search.

Mixture of Themes mode. To ensure thematic diversity in the generated question while also guaranteeing recency and search dependence, we sample $\mathcal{T}_{\text{sample}} \sim \text{Uniform}(\mathcal{T})$ with $|\mathcal{T}_{\text{sample}}| = k$, $k \in \{5, 6, 7\}$. For each $t \in \mathcal{T}_{\text{sample}}$, the generator (either $\mathcal{M}_1$ or $\mathcal{M}_2$) issues live queries to retrieve recent and/or obscure facts, with the constraint that at least one fact references information post–2024-01-01. The generator then composes a multi-hop question q by logically chaining the k facts—one hop per theme—into a coherent reasoning path

Seeded Question mode. To approximate real-world query distribution and logical chaining patterns observed in hard multi-hop questions, we construct a seed bank of 100 questions (50% manually authored; 50% from **BrowseComp** [30]). For each seed q_0, we sample candidate themes $\{t_1, \ldots, t_k\} \subset \mathcal{T}$ with $k \in \{3, 4, 5\}$ and rewrite q_0 into a new question q by integrating one or more sampled themes that satisfy the obscurity/recency constraints while preserving the seed's multi-hop scaffold / logical chaining patterns.

Data obfuscation To remove surface cues that let models *short-circuit* the intended multi-hop reasoning, we apply a dedicated obfuscation pass after question generation. Using the non-search model $\mathcal{M}_3$ (GPT-4o) under an in-context learning setup with exemplars, we paraphrase the question to mask intermediate hops. Concretely, $\mathcal{M}_3$ softens exact anchors in each hop by (i) converting specific dates to coarse intervals ("March 2025" $\rightarrow$ "early 2025"), (ii) mapping precise numerics to qualitative magnitudes ("1%" $\rightarrow$ "negligible"), (iii) replacing named entities with indirect descriptors ("University of Florida" $\rightarrow$ "a major southeastern university"), and (iv) embedding causal/comparative pivots as descriptors rather than explicit connectors. These edits suppress shortcut signals without altering the underlying facts that must be recovered via search.

Multi-agent Verification After the obfuscation pass, we validate that each QA pair remains both *answerable* and *search-dependent*. We retain (q, a) only if the two search-enabled LRMs are able to answer the question correctly while a strong non-search baseline fails, i.e., $\mathcal{M}_1^{\text{search}}(q) = \mathcal{M}_2^{\text{search}}(q) = a \neq \mathcal{M}_3^{\text{no-search}}(q)$. This post-obfuscation check enforces correctness via cross-model agreement and certifies that web retrieval is necessary; it also filters cases where paraphrasing either leaked the answer or inadvertently made the item unsolvable.

2.2 Agentic Reinforcement Learning

In this section, we formulate multi-turn, tool-augmented RL with LLM policies. Let $x \in \mathcal{X}$ be an input sampled from a data distribution $\mathcal{D}$, and let $\mathcal{T}$ denote the set of available tools. The policy

LLM π_θ interacts with tools to produce a *reasoning trajectory* $\mathcal{R}$ interleaved with tool-call feedback, followed by a final textual answer y. We include a reference policy π_{ref} for KL regularization, a verifiable reward function r_ϕ (parameterized LLM as judge), and a KL weight $\beta > 0$. We optimize a KL-regularized expected reward:

$$\max_{\pi_\theta} \mathbb{E}_{x\sim\mathcal{D},\,(\mathcal{R},y)\sim\pi_\theta(\cdot\,|\,x;\mathcal{T})}\Big[r_\phi(x,\mathcal{R},y)\Big] \;-\; \beta\,\mathbb{D}_{\text{KL}}[\pi_\theta(\mathcal{R},y\mid x;\mathcal{T})\,\|\,\pi_{\text{ref}}(\mathcal{R},y\mid x;\mathcal{T})]\,. \quad (1)$$

Unlike conventional RL over pure text rollouts, agentic RL interleaves tool feedback into the *reasoning* process. We decompose the joint sampling as where $\mathcal{R} = \{\mathcal{R}_t\}_{t=1}^{t_\mathcal{R}}$ is the reasoning trajectory of length $t_\mathcal{R}$, interleaved with tool-call responses, and $y = \{y_t\}_{t=1}^{t_y}$ is the final answer of length t_y. Each reasoning step t can be viewed as a tuple

$$P_\theta(\mathcal{R},y\mid x;\mathcal{T}) = \Big[\prod_{t=1}^{t_\mathcal{R}} P_\theta(\mathcal{R}_t\mid\mathcal{R}_{<t},x;\mathcal{T})\Big]\cdot\Big[\prod_{t=1}^{t_y} P_\theta(y_t\mid y_{<t},\mathcal{R},x;\mathcal{T})\Big],\quad \mathcal{R}_t=(\varphi_t,c_t,o_t). \quad (2)$$

where φ_t is a latent "`think`" segment generated by the policy model enclosed in within the `<think></think>`, $c_t \in \mathcal{T}$ represents the chosen tool and its arguments enclosed within `<tool_call></tool_call>` tags and o_t is the "`response`" returned by the environment enclosed in the `<tool_response></tool_response>`, based on the ReAct template.

Optimization via GRPO. In practice, we optimize (1) with a token-level clipped surrogate. For a prompt-group of G sampled rollouts with scalar rewards $\{R_i\}_{i=1}^G$, we define group-relative advantages in (3)

$$\hat{A}_{i,t} \;=\; \frac{R_i-\mu_R}{\sigma_R},\quad \mu_R=\tfrac{1}{G}\sum_{j=1}^{G}R_j,\quad \sigma_R=\sqrt{\tfrac{1}{G}\sum_{j=1}^{G}(R_j-\mu_R)^2}. \quad (3)$$

and and minimize the clipped loss as defined in (4)

$$\mathcal{L}_{\text{GRPO}} = \frac{1}{G}\sum_{i=1}^{G}\frac{1}{T_i}\sum_{t=1}^{T_i}\min\Big[r_{i,t}\,\hat{A}_{i,t},\ \text{clip}\big(r_{i,t},1{-}\epsilon,1{+}\epsilon\big)\,\hat{A}_{i,t}\Big],\qquad r_{i,t}=\frac{\pi_\theta(o_{i,t}\mid x,\mathcal{H}_{t-1})}{\pi_{\theta_{\text{old}}}(o_{i,t}\mid x,\mathcal{H}_{t-1})}. \quad (4)$$

where the trajectory level reward in multi-turn RLVR setting is defined as follows

$$r_i \;=\; \alpha\,R_i^{\text{format}} \;+\; (1-\alpha)\,R_i^{\text{answer}},\qquad \alpha\in[0,1] \quad (5)$$

Specifically, the format score R_i^{format} verifies whether the rollout trajectory follows the ReAct template; the answer score R_i^{answer} uses an LLM-as-judge to determine whether the final prediction matches ground truth.

2.3 Agentic Tool Design

We provide our policy model access to two tools for goal-conditioned web retrieval and reading. At step t, the agent emits $\mathcal{R}_t = (\varphi_t, c_t, o_t)$, where φ_t is latent `think` content, c_t is a tool call with arguments, and o_t is the tool response.

`search_urls` **(web search).** The tool takes as input a natural language query q and returns a ranked list of triples $(u, \texttt{title}, \texttt{snippet})$ using a live search engine. The policy uses this to identify promising sources and optionally select a URL u for opening in the next step. The tool is invoked as follows: `<tool_call>{name: search_urls, args: {query: q}}</tool_call>`

`query_url` **(goal-conditioned page reading).** Given a goal g and a URL u, the tool leverages an LLM to return targeted evidence-backed response that address g. This tool enables precise grounding of facts and targeted querying of web-pages. Compared to the injestion of entire web-page into the policy model's trajectory, this tool minimizes noise and increases recall. The tool is invoked as follows: `<tool_call>{name: query_url, args: {goal: g, url: u}}</tool_call>`

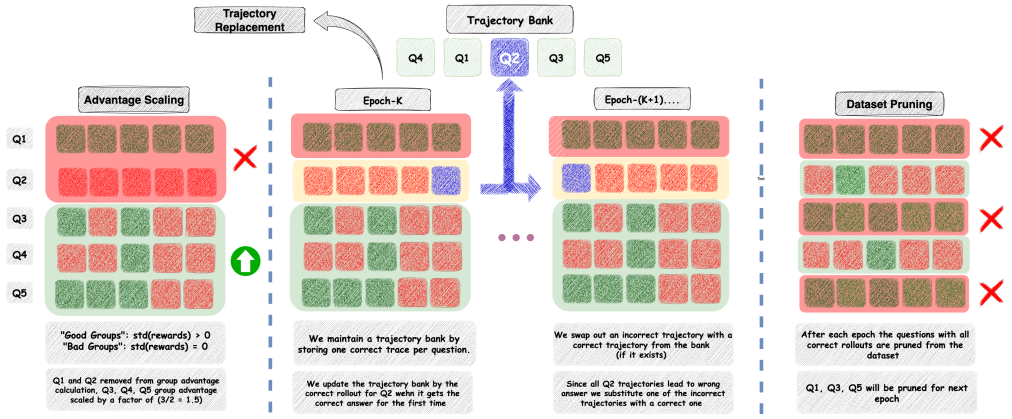

Figure 4: Visualzation of key ideas adapted by RAPO to stabalize GRPO training in multi-turn tool interaction scenarios. In-order (L-geR): i.) Advantage Scaling (Batch level), ii.) Trajectory Replacement(Group Level), & iii.) Dataset Pruning(Epoch Level)

2.4 RAPO: Reward Aware Policy Optimization

RAPO is a lightweight extension of GRPO that stabilizes multi-turn, tool-augmented training by mitigating the challeneges mentioned in Section. 1. Let σ_R be the within-group reward standard deviation from (3); a group is **Good** if $\sigma_R > 0$ and **Bad** if $\sigma_R = 0$. As Bad groups become more prevalent, either because all rollouts for a prompt converge to the correct answer (prompt saturation) or because multi-turn cascading of errors drive all rollouts to failure, the batch increasingly spends compute on rollouts that carry no advantage signal, causing the effective gradients to shrink, hence destabilizing updates. RAPO applies three targeted modifications (on top of GRPO to counter precisely these effects with zero additional rollout cost.

Dataset pruning. We remove prompts at the end of every epoch that are effectively solved to avoid spending compute on groups that produce no training signal. This early-exit rule boosts throughput and implicitly induces a curriculum: as training progresses, the active set concentrates on harder prompts

$$\text{SolveRate}(q) \;=\; \frac{1}{G}\sum_{i=1}^{G}\mathbf{1}[R_i > 0], \qquad \text{prune if } \text{SolveRate}(q) \geq 0.9 \tag{6}$$

Advantage scaling. When the proportion of Bad groups increase in a batch the magnitude of gradient norm decreases, as these Bad groups contribute no gradient signal. This causes the total gradient norm across the batch to collapse, causing ineffective and unstable training updates.To preserve the overall gradient magnitude, we reweight the token-level advantages of Good groups inversely by their batch frequency:

$$\tilde{A}_{i,t} \;=\; \frac{G}{G_{\text{good}}}\cdot \hat{A}_{i,t}, \qquad G_{\text{good}} = \#\{\sigma_R > 0\}\,. \tag{7}$$

This preserves the magnitude of gradient updates without incurring additional rollout computation costs as done in DAPO, which effectively keeps regenerating trjectories untill it fills a batch with Good groups.

Replay buffer. To rescue Bad groups with all failed rollouts for a prompt, we keep a per-prompt buffer $\mathcal{B}$ with the most recent successful rollout $\mathbf{o}^\star$ (where $R(q,\mathbf{o}^\star) > 0$). If the current group for q fully fails, we overwrite one of uniformly sampled rollout of the group with $\mathbf{o}^\star$:

$$\big(j \sim \text{Uniform}\{1,\ldots,G\},\; \mathbf{o}_j \leftarrow \mathbf{o}^\star\big). \tag{8}$$

This guarantees at least one successful trajectory in the group, restoring variance ($\sigma_R > 0$) and enabling RAPO's relative advantage computation to penalize failed completions. Beyond gradient

recovery, the successful trajectory also anchors the group with a high-quality, low-entropy reference, improving stability in the presence of distributional drift.

2.5 Steerable Step-Level Reward Design for Search Tools

We design a novel *Steerable Step-Level Reward* that alleviates the challenges faced by RLVR training in the multi-turn, tool-interaction setting using vaniila reward (5) as described in Section 1. The reward enables us to steer (i) *how much* the agent uses tools and (ii) *how* it allocates cognition to exploration and verification. Starting from the vanilla RLVR objective in (5), we make the correctness branch R_i^{answer} depend on novelty-aware labels assigned by a GPT-4.1 LLM-as-judge to each call c_t in $\mathcal{R} = \{(\varphi_t, c_t, o_t)\}_{t=1}^{T}$ as follows:

`search_urls` $\in \{$
UNIQUESEARCH: (semantically new query on unseen entities/facets),
REDUNDANTSEARCH: (near-duplicate of a prior query; overlapping results)$\}$

`query_url` $\in \{$
EXPLORATION: (first read of a new URL),
VERIFICATION: (cross-source check on a different URL for an existing claim; allowed B_v times),
REDUNDANTQUERY: (further checks beyond B_v)$\}$

From the LLM-as-Judge tool call classificaiton we form tallies as follows:

$$n_{\text{uniqS}},\ n_{\text{redS}},\ n_{\text{explore}},\ n_{\text{verify}},\ n_{\text{redQ}}, \quad n_{\text{uniqQ}} \ = \ n_{\text{explore}} + n_{\text{verify}}, \quad T \ = \ |\mathcal{R}|\,. \tag{9}$$

and define the following aggregates:

$$\rho \ = \ \frac{n_{\text{redS}} + n_{\text{redQ}}}{T}, \qquad \Delta_S \ = \ n_{\text{uniqS}} - n_{\text{redS}}, \qquad \Delta_Q \ = \ n_{\text{uniqQ}} - n_{\text{redQ}}. \tag{10}$$

Using these summaries we define our *Steerable Step-Level Reward* as:

$$r_i \ = \ \begin{cases} \alpha\, R_i^{\text{format}} \ + \ \max\big((1-\alpha)(1-\rho),\, 0.5\big), & \text{if } R_i^{\text{answer}} = 1, \\ \alpha\, R_i^{\text{format}} \ + \ c_1\, \min\big(1, \frac{\Delta_S}{C_S}\big) \ + \ c_2\, \min\big(1, \frac{\Delta_Q}{C_Q}\big), & \text{if } R_i^{\text{answer}} = 0, \end{cases} \tag{11}$$

We set $\alpha = 0.1$ and $c_1 = c_2 = 0.2$ ($c_1{+}c_2 = 0.4$), to ensure any incorrect rollout has $r_i \leq 0.5$, while any correct rollout has $r_i \geq 0.5$, which ensures incorrect trajectories never get rewarded more than the correct ones. We set $c_1{=}c_2$, to allow equal weight to `search_urls` (Δ_S) and `query_url` (Δ_Q).

Steerability. We expose three primary knobs: (i) C_S and (ii) C_Q set the saturation thresholds for creditable novelty in `search_urls` and `query_url`, respectively. Increasing C_S and/or C_Q raises the novelty caps, enabling more steps to earn credit when they introduce genuinely new evidence; decreasing them compresses trajectories. (iii) The per-claim verification budget B_v controls verification depth: higher B_v permits multiple creditable cross-checks per claim, promoting verification. For our experiments we set B_v = 1 allowing 1 cross-check per claim, additionally we set C_S = 8 and C_Q = 16.

2.6 Training Recipe

We build our reinforcement learning with verifiable rewards (RLVR) framework on top of RECALL [3]. For web search, we use the Serper API [21], and implement a retrieval toolchain leveraging Jina-AI together with open-source components such as TRAFILTURA and CRAWL4AI. Training is carried out in two stages.

Stage 1. We train with RAPO for 10 epochs on our curated DUETQA dataset, comprising **4,988** high-quality QA instances. The setup uses a constant learning rate of 1×10^{-6} with the Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.95$), batch size 32, mini-batch size 16, 5 rollouts per group, and top-$p = 1.0$ sampling. Each rollout is capped at 32 tool-interaction steps, with each step limited to 8,192 output tokens. The vanilla reward ((5)) is used to instill correct tool-calling behavior and strict format adherence.

Stage 2. We continue RLVR training for an additional 2 epochs under the same hyperparameter settings. For Stage 2, we construct a mixed dataset by combining DUETQA, with math data from S1 dataset [15], and the training split of MUSIQUE [28]. This combined pool is adversarially filtered against the Stage-1 checkpoint, yielding **5,077** instances. From MUSIQUE, we retain only questions requiring at least three reasoning hops to ensure sufficient compositional depth. For this stage, we adopt the Steerable Step-Level Reward ((11)) to extend the tool-use horizon beyond 20 calls in a stable manner.

We use the Qwen3-4B model [33] as the base, which supports a maximum context length of $40{,}960$ tokens; we utilize the full window during training. A higher sampling temperature of 1.4 is applied to Qwen3 models, consistent with prior findings [2]. All experiments are conducted on a single node with $8\times$H100 GPUs.

3 Experiments

3.1 Baselines

We benchmark our models against leading open-source DeepSearch agents with public checkpoints:

Jan-nano [4] is a Qwen3-4B model post-trained on MuSiQue using staged DAPO to sequentially improve tool use, answer quality, and context handling with simulated search/query tools. **ZeroSearch** [26] fine-tunes Qwen2.5-3B/7B-Instruct via response finetuning (RFT) with an LLM simulating search APIs. We evaluate both sizes at temperature 0. **Search-o1** [14] is training-free, combining search + query tools and returning the first fully scraped page; we use its default settings (temp. 0.7, repetition penalty 1.05). **R1-Searcher** [25] fine-tunes Qwen2.5-7B-Base on HotpotQA and 2WikiMultiHopQA, using GPT-4o-mini to query webpages (Wikipedia-only in the original). We run with temp. 0.7. **WebSailor** [13] is RL-trained on curated web-crawl data with cold-start finetuning followed by DUPO. It separates search/query, with Qwen2.5-72B-Instruct as the query LLM. For closed-source comparison, we include [17, 16]. All baselines are tested under dynamic multi-step reasoning with context windows of 32,768 (Qwen2.5) or 40,960 (Qwen3, run in "thinking mode"). Metrics are Pass@1 scores judged by GPT-4.1-mini. We evaluate across 10 benchmarks: 5 in-domain DeepSearch tasks and 4 general reasoning tasks. DeepSearch benchmarks stress retrieval and reasoning over multi-hop, heterogeneous sources: **SimpleQA** [29] (4,326 single-hop web questions), **FRAMES** [12] (824 2–3 hop diverse-format queries), **WebWalkerQA** [31] (680 multi-page traversal tasks), **Seal0** [18] (111 noisy/conflicting queries), and **MuSiQue** [28] (2,417 Wikipedia multi-hop questions). General reasoning benchmarks probe out-of-domain generalization: **HLE** [19] (2,500 mixed-subject questions), **AIME-25** [1] (30 olympiad-level math problems), **GPQA-Diamond** [20] (198 "Google-proof" expert science MCQs), and **MedQA** [10] (1,266 medical licensing exam questions).

3.2 Results

Fathom-Search sets new state-of-the-art on Deep Search benchmarks. As evident from Table 1, Fathom-Search-Stage-2 outperforms all prior open baselines across parameter classes. In the $\leq$4B tier, it achieves **52.1%** on DeepSearch and **53.8%** on General Reasoning, +24.6 pp and +4.0 pp jump over **Qwen3-4B +Search**. We highlight around 100% gain in specific hard benchmarks like **FRAMES**, **WebWalker** and more than 3x on **Seal0**. We also get higher results than **II Search 4B** across all benchmarks. Fathom-Search-Stage-2 also outperforms works on top of larger Qwen2.5-7B like ZeroSearch-7B and R1-Searcher-7B.

Generalization across domains. Unlike most models that drop on out-of-distribution tasks, Fathom-Search generalizes well. On GPQA-D and MedQA, Fathom-Search-Stage-2 achieves **60.1%** and **75.4%**, surpassing WebSailor-3B and ZeroSearch-3B by +23–25 pp. This reflects strong transfer despite no domain-specific finetuning.

Competing with closed source models. Fathom-Search-Stage-2 outperforms GPT-4o +search on prominent benchmarks like **SimpleQA, FRAMES, WebWalker, HLE and GPQA-Diamond**. We are 18.4 absolute pp higher on **WebWalker** and 7 points on **Seal0** and **GPQA-Diamond** each. We are also 2x more accurate on hard general reasoning benchmark **HLE**.

Table 1: **Main results.** Accuracy (%) on DeepSearch benchmarks SimpleQA, FRAMES, WebWalker, Seal0, Musique and general reasoning benchmarks HLE, AIME-25, GPQA-D, MedQA. 'Avg' is the unweighted mean within each block. Bold/italics denote best/second-best per benchmark.

	DeepSearch Benchmarks						General Reasoning Benchmarks				
Model	**SimpleQA**	**FRAMES**	**WebWalker**	**Seal0**	**Musique**	**Avg**	**HLE**	**AIME-25**	**GPQA-D**	**MedQA**	**Avg**
Closed-source Models											
GPT-4o (without search)	34.7	52.4	3.2	7.2	34.0	26.3	2.3	71.0	*53.0*	88.2	53.6
o3 (without search)	49.4	43.2	14.0	14.0	48.9	33.9	*20.3*	88.9	*85.4*	95.4	72.5
GPT-4o (with search)	*84.4*	*63.7*	*31.6*	*15.3*	*37.5*	*46.5*	4.3	*71.0*	53.0	*88.2*	*54.1*
o3 (with search)	**96.0**	**86.8**	**57.0**	**49.5**	**51.2**	**68.1**	**27.4**	**88.9**	**85.4**	**95.4**	**74.3**
Open-source Models											
Qwen-2.5-7B	3.96	16.5	2.1	1.4	6.2	6.0	1.2	10	33.0	61.2	24.7
Qwen-2.5-7B + Search	50.8	23.3	10.1	3.0	13.6	20.2	2.4	10	33.5	62.0	25.3
Qwen3-4B	3.8	14.7	2.6	2.1	9.0	6.4	4.2	65.0	55.1	71.0	48.8
Qwen3-4B + Search	67.7	27.2	17.5	6.2	18.7	27.5	6.2	65.0	55.9	72.0	49.8
ZeroSearch-3B	51.9	11.3	8.7	7.1	13.8	18.6	3.4	10.0	14.6	51.0	17.3
ZeroSearch-7B	75.3	30.0	18.2	6.2	20.6	30.1	4.2	10.0	29.3	57.5	22.8
Search-R1-7B	58.8	37.0	1.8	1.4	19.1	23.6	2.1	10.0	33.3	56.5	25.5
o1-search (Qwen3-4B)	57.5	26.8	10.8	5.5	15.3	23.2	3.4	40.0	30.5	53.7	31.9
WebSailor-3B	87.1	44.4	**52.2**	9.0	27.4	44.0	7.4	40.0	45.5	51.3	36.0
Jan-Nano-128K	83.2	43.4	33.7	6.2	23.9	38.1	6.1	53.3	51.0	65.4	44.0
Jan-Nano-32K	80.7	36.1	25.0	6.2	21.4	33.9	5.5	60.0	37.4	66.0	42.2
II-Search-4B	*88.2*	*58.7*	*40.8*	*17.1*	*31.8*	*47.3*	*7.4*	*60.0*	*51.5*	*72.1*	*47.8*
Fathom-Search-4B (Stage-1)	88.1	57.2	39.0	19.8	31.3	47.1	6.7	60.0	55.6	75.4	49.4
Fathom-Search-4B (Stage-2)	**90.0**	**64.8**	*50.0*	**22.5**	**33.2**	**52.1**	**9.5**	**70.0**	**60.1**	**75.4**	**53.8**

Table 2: Effect of swapping the Query-LLM for a fixed RAPO-trained search policy. Using GPT-4.1-mini as the reader yields consistent gains, especially on the retrieval-heavy WebWalkerQA benchmark.

Query LLM	**SimpleQA**	**FRAMES**	**WebWalkerQA**	**GPQA-D**
Qwen3-4B Stage-1 (RAPO)				
Qwen3-4B	85.1	56.3	35.8	55.1
GPT-4.1-mini	86.6	57.2	39.0	56.6

On the Choice of query LLM Table 2 presents an evaluation of two prominent query LLM configurations: (i) search-o1: using the same model as the policy model (i.e., Qwen3), and (ii) using a stronger API-based LLM such as GPT-4.1-mini. The comparison is conducted under a fixed RAPO-trained policy model. Across all benchmarks, API-based querying of webpages with GPT-4.1-mini yields marginal yet consistent improvements over smaller models like Qwen3.

4 Conclusion

We introduce Fathom-Search-4B and a practical post-training recipe that jointly tackles reward-sparsity, optimization instability, and shallow tool use in web-grounded reasoning. Our DUETQA multi-agent self-play corpus, two-stage RL-Zero training with RAPO, and steerable step-level rewards stabilize multi-turn learning and reliably extend tool use beyond 10 steps, fostering disciplined exploration and verification. The resulting agent attains state-of-the-art results on DeepSearch benchmarks while transferring competitively to STEM and medical evaluations, with ablations validating the gains from goal-conditioned retrieval and stronger reader LLMs. We view this as a concrete, scalable step toward dependable, autonomous DeepResearch agents.

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Table 3: Ablation on using GRPO as the training algorithm for Stage-1 compared to RAPO shows RAPO's superior performance on DeepSearch tasks.

Algorithm	SimpleQA	FRAMES	WebWalkerQA	Seal0
Qwen3-4B Stage-1 (GRPO)	87.8	55.2	33.8	14.41
Qwen3-4B Stage-1 (RAPO)	88.1	57.2	39.0	19.8

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