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SEALQA: RAISING THE BAR FOR REASONING IN SEARCH-AUGMENTED LANGUAGE MODELS

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ABSTRACT

We introduce SEALQA, a challenge benchmark for evaluating SEarch-Augmented Language models on fact-seeking questions where web search yields conflicting, noisy, or unhelpful results. SEALQA comes in three flavors: (1) SEAL-0 (main) and (2) SEAL-HARD, which assess factual accuracy and reasoning capabilities, with SEAL-0 targeting the most challenging questions where frontier non-reasoning models (e.g., GPT-4.1) achieve near-zero accuracy; and (3) LONGSEAL, which extends SEALQA to test long-context, multi-document reasoning in "needle-in-ahaystack" settings. Our evaluation reveals critical limitations in current models. Even frontier reasoning models face significant challenges across SEALQA flavors. On SEAL-0, GPT-5 with tools achieves only 43.2% accuracy at its best reasoning effort. We also find that even advanced reasoning models (e.g., DEEPSEEK-R1) can be vulnerable to noisy search results. *Notably*, increasing test-time compute does not yield reliable gains across GPT-5 and the o-series of models, with performance often plateauing or even declining early. Finally, while current models are less affected by the "lost-in-the-middle" issue, they still fail to reliably identify relevant documents in LONGSEAL when faced with numerous distractors. To facilitate future work, we release SEALQA at anonymous. 4 open.science/r/SealQA.

Introduction

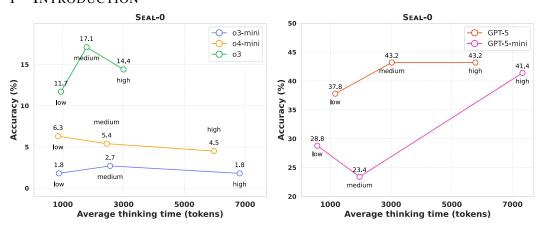


Figure 1: Frontier model performance before (left) and after (right) the release of SEAL-0. Despite potential data contamination or direct access by agentic models, SEAL-0 continues to pose a significant challenge for current frontier LLMs. Test-time scaling does not lead to reliable gains, with performance often plateauing or even declining early. See Figure 6 in Appendix A for SEAL-HARD results.

Large language models (LLMs) have entered a new scaling paradigm: test-time scaling, where models dynamically allocate more compute during inference time to improve performance (OpenAI, 2025a; Google, 2025; xAI, 2025; Anthropic, 2025). This paradigm shift is embodied in reasoning models, which leverage reinforcement learning and other techniques to guide inference-time strategies such as chain-of-thought reasoning, recursive refinement, and real-time search (Muennighoff et al., 2025; Guo et al., 2025; Snell et al., 2024; Geiping et al., 2025). These models can now decompose questions into subqueries, decide when and how to query a search engine, and fuse retrieved content into structured reasoning paths (OpenAI, 2025a; Google, 2025; Jin et al., 2025).

As LLMs advance, benchmarks that rely on static knowledge and simple reasoning become saturated and fail to keep pace. For example, frontier models now achieve over 90% accuracy on MMLU (Phan et al., 2025). Furthermore, most evaluations of search-augmented LLMs focus on short factual queries that top-ranked results answer directly (Vu et al., 2024; Kasai et al., 2023). These setups require only shallow comprehension and fail to reflect the messy, ambiguous nature of real-world search.

To properly evaluate today's LLMs, benchmarks that go beyond simple fact lookup are needed. Real-world search often returns documents that are outdated, misleading, or superficially relevant but ultimately unhelpful. Navigating this noise requires deeper reasoning that filters inconsistencies, reconciles contradictions, and identifies trustworthy signals. Benchmarks that simulate these challenges are rare, partly because they are difficult to curate and validate at scale.

We introduce SEALQA, a *small* but *extremely challenging* benchmark (see Figure 2) for evaluating search-augmented LLMs on fact-seeking questions. Each SEALQA question is carefully crafted by NLP researchers to trigger ambiguous, conflicting, or noisy search results (see Figure 3). This design makes it difficult to answer questions through simple keyword matching or by relying on top-ranked documents. SEALQA spans a range of ques-

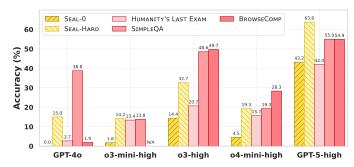


Figure 2: Accuracy of LLMs across benchmarks. SEALQA poses significant challenges to frontier models.

tion types, including time-sensitive questions, across diverse domains such as science, technology, sports, entertainment, politics, history, geography, etc.

SEALQA questions probe a broad spectrum of complex reasoning skills. These include distinguishing between similar entities or events, tracking changes to the same entity over time, interpreting information embedded in search-result plots, charts, or tables, counting multiple items, reasoning over non-English content, and debunking false premises or common misconceptions (see Figure 7 in Appendix B for sample questions). All questions are self-contained, verifiable, and require intensive reasoning to resolve ambiguity, filter misinformation, or reconcile conflicting evidence. These capabilities are central to modern LLMs but are not adequately captured by existing benchmarks.

To ensure both difficulty and quality, each SEALQA question undergoes a *rigorous* multi-round vetting process: an initial phase with two or more graduate-level reviewers, followed by expert approval. SEALQA comes in *three flavors*:

- SEAL-0 (*main*; 111 questions): A carefully curated core set where frontier non-reasoning models like GPT-4.1 with browsing consistently fail. Each question is iteratively refined until multiple models fail across several attempts (0% accuracy, hence the "0" in the name).
- SEAL-HARD (254 questions): A broader set that includes SEAL-0 and additional difficult questions that did not meet our strict failure threshold but remain highly challenging.
- LONGSEAL (254 questions): A "needle-in-a-haystack" variant that tests long-context, multi-document reasoning. Each question is paired with a large set of retrieved documents, among which only one contains or implies the correct answer. This document is buried within irrelevant, noisy, or misleading content.

We intentionally kept SEALQA small due to the high cost and complexity of question development.¹ Building the full benchmark required a team of *six* NLP researchers working over *eight* months through multiple development cycles. A smaller benchmark also reduces API evaluation costs, allows more frequent updates, and aligns with recent emphasis on high-quality, targeted evaluations over large, noisy ones (Rein et al., 2024; Maia Polo et al., 2024).² SEALQA is also designed for stable evaluation with *low* run-to-run variance.³

¹Each question required over an hour on average – roughly 45 minutes to draft, plus additional time for review and revision. Many initial ideas were discarded as they failed to meaningfully challenge frontier LLMs.

²For example, the widely used GPQA-DIAMOND (Rein et al., 2024), a compact set of 198 expert-vetted questions, demonstrates how a small, carefully curated dataset can effectively assess a model's reasoning ability.

³Our questions often lead multiple models to fail across repeated attempts.

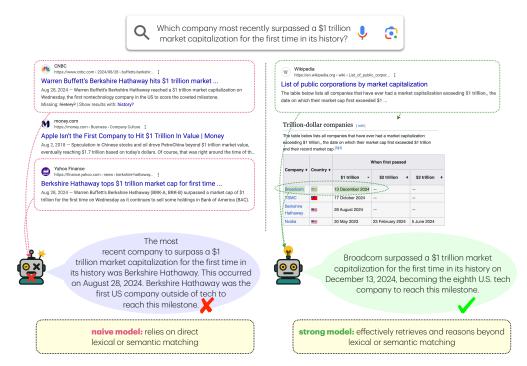


Figure 3: SEALQA requires intensive reasoning to resolve ambiguity, filter out misinformation, or reconcile conflicting evidence. See Appendix H for sample model outputs.

Our key contributions are as follows: (1) We introduce SEALQA, a challenge benchmark designed to evaluate reasoning under noisy, conflicting, and ambiguous search results. SEALQA includes three flavors: SEAL-0, SEAL-HARD, and LONGSEAL, each targeting different challenges in search-augmented reasoning; (2) We benchmark a range of LLMs and uncover significant limitations in current retrieval-augmented approaches. Even *state-of-the-art* models struggle across SEALQA flavors when faced with conflicting or misleading context. On SEAL-0, performance remains low even for agentic models equipped with search tools. We also find that advanced reasoning models can be highly vulnerable to noisy search results. *Notably*, increasing test-time compute does not reliably improve performance across OPENAI's GPT-5 and o-series of models – performance often plateaus or declines. LongSEAL further reveals major weaknesses in long-context reasoning: while current frontier LLMs are more robust to "lost-in-the-middle" effects (Liu et al., 2024), they still fail to reliably identify and prioritize relevant evidence amid distractors; and (3) We publicly release SEALQA as a dynamic, versioned benchmark, and commit to review and update its answers regularly to ensure that evaluations reflect the most recent knowledge.

2 Data collection

In this section, we describe SEALQA, our benchmark designed to capture the complexity of real-world information-seeking. SEALQA rigorously evaluates a model's reasoning ability, robustness to noisy search results, and capacity to handle dynamic, real-world knowledge.

Human annotators: To build SEALQA, we recruited NLP researchers⁴ as human annotators who were shown a diverse set of exemplars that illustrated the types of questions we sought to collect.

Question types: Our questions span several categories: (Q_1) advanced reasoning, which covers multi-hop reasoning, interpreting search-result plots, charts, or tables, and performing counting or calculations; (Q_2) entity/event disambiguation, which focuses on distinguishing between similar entities or events; (Q_3) temporal tracking, which requires identifying and differentiating instances of entities over time; (Q_4) cross-lingual reasoning, where the question is in English but answering it requires retrieving and reasoning over non-English sources; and (Q_5) false-premise questions, which require debunking false assumptions.

⁴including the authors and their colleagues

Annotation criteria: Annotators were instructed to write questions with a *single*, *unambiguous* answer (e.g., specifying "on what date" rather than asking "when"). Each question must be supported by one or more webpages that justify the reference answer, which ensures *verifiability*. For questions that involve *fresh knowledge*, annotators were required to cite regularly updated sources to support future answer updates. We also classify questions by *freshness* (Vu et al., 2024): *never-changing* (NEVER; answers never change), *slow-changing* (slow; answers change over several years), and *fast-changing* (FAST; answers typically change within a year). All questions were designed to appear natural while still triggering ambiguous, conflicting, or misleading search results when entered into a search engine like GOOGLE. Each question has a predefined annotation that classifies its expected search results as CONFLICT. (mixed correct and misleading answers) or UNHELPFUL (no correct answers). Annotators also provided explanations for each answer, including any necessary clarification or subtle reasoning. Finally, each question was refined until it consistently caused multiple models to fail across repeated attempts.

Quality control: We employed a rigorous multi-round review process. Each question was first reviewed by two or more graduate-level annotators, followed by expert approval. We performed several rounds of data cleaning, including verification of supporting URLs, answer correctness, and question clarity. Questions whose answers change too frequently were excluded. For each question, we also annotated the effective year (when the answer last changed) and the expected next review date to support future maintenance.

Diversity: SEALQA questions vary in length, with an average of 31 tokens and a maximum of 69. SEALQA also spans diverse domains: science and technology (26.8%), sports (22.0%), entertainment (21.7%), politics (9.1%), history and geography (8.3%), and others (12.2%).⁵ By question category, 72.4% involve advanced reasoning (Q_1), 58.3% entity/event disambiguation (Q_2), 13.7% temporal tracking (Q_3), 5.5% cross-lingual reasoning (Q_4), and 4.3% false-premise detection (Q_5). By freshness, 31.1% are *never-changing*, 43.7% *slow-changing*, and 25.2% *fast-changing*. By effective year, 22.0% reference 2025 events, 19.3% 2024, and 58.7% prior to 2024.

Curation of SealQA flavors: To curate Seal-0, we tested each question against GPT-40, GPT-4.1, their mini variants (OpenAI, 2024a;b; 2025c), and Llama-4-Scout (Meta, 2025), both with and without browsing. Only questions whose answers all models failed to produce across 10–15 attempts were retained. This follows current practices for constructing challenging benchmarks; for example, SIMPLEQA (Wei et al., 2024) was also adversarially collected against GPT-4 responses. Seal-0 was then combined with other rejected-but-difficult questions to form Seal-Hard.

For LongSeal, each Seal-Hard question is paired with a set of retrieved documents: *one* helpful (gold) document from annotator-provided webpages, and up to 50 hard negatives that appear relevant but are unhelpful.⁷ To ensure difficulty, we used GPT-40 MINI to filter out negatives whose content might allow the correct answer to be inferred. The gold document was randomly inserted among the negatives. LongSeal contains over 7.6K documents and serves as a testbed for long-context reasoning under noisy retrieval conditions.

Evaluation protocol: Models are evaluated using a GPT-40 MINI auto-rater adapted from Wei et al. (2024), which takes the question, predicted answer, and reference answer as input and labels responses as "correct", "incorrect", or "not attempted" (see Appendix C for the full prompt). The evaluation follows a relaxed protocol that checks whether the main answer is factually correct and consistent throughout the response.

Auto-rater reliability: To assess the auto-rater's reliability, two authors independently evaluated 100 answers. Disagreements were resolved through discussion, which produced a unified set of human ratings that agreed with the auto-rater 98% of the time.

⁵Following Wei et al. (2024), topic labels were assigned post-hoc using GPT-40 MINI.

⁶We applied FreshPrompt (Vu et al., 2024) to Llama-4-Scout.

⁷To collect hard negatives, we used Google to retrieve the top 10 webpages per question and extracted their main content using Trafflatura (Barbaresi, 2021). To add temporal diversity and potential conflicts, we retrieved 10 more pages restricted to pre-2023 content. We also used GPT-40 MINI to generate three semantically related queries per question and collected documents for each. Duplicates were removed, and documents whose length exceeded 10K tokens were excluded.

Table 1: Accuracy on Seal-0 and Seal-Hard. Frontier LLMs face significant challenges on SealQA questions. † indicates results using ChatGPT's built-in search; all other search-based results use FreshPrompt (Vu et al., 2024). * indicates evaluation conducted after the release of SealQA.

Model	knowl.	type	SEA	L-0	SEAL-	HARD			
Woder	cutoff	type	w/o search	w/ search	w/o search	w/ search			
Closed-source models									
GPT-40-MINI	Sep 30, 2023	Снат	0.0	0.0^{\dagger}	9.1	13.4^{\dagger}			
GPT-4.1-MINI	May 31, 2024	Снат	0.0	0.0^{\dagger}	13.8	11.8^{\dagger}			
GPT-40	Sep 30, 2023	Снат	0.0	0.0^{\dagger}	11.8	15.0^{\dagger}			
GPT-4.1	May 31, 2024	Снат	0.0	0.0^{\dagger}	15.0	20.5^{\dagger}			
o3-mini-high	Sep 30, 2023	REASON.	3.6	1.8	12.6	14.2			
O4-MINI-HIGH	May 31, 2024	AGENTIC	-	4.5 [†]	-	19.3^{\dagger}			
о3-нібн	May 31, 2024	AGENTIC	-	14.4^{\dagger}	-	32.7^{\dagger}			
GPT-5-MINI-HIGH *	May 31, 2024	REASON.	6.3	41.4^{\dagger}	16.9	60.2^{\dagger}			
GРТ-5-ніGН *	Sep 30, 2024	REASON.	15.3	43.2^{\dagger}	37.8	63.8 [†]			
	Open	ı-weight mod	dels						
LLAMA-3.2-3B	December 1, 2023	Снат	0.0	0.0	1.6	3.5			
LLAMA-3.1-70B	December 2023	Снат	0.0	0.0	0.0	6.3			
LLAMA-4-SCOUT-17B-16E (109B)	August 2024	Снат	0.0	0.0	5.9	5.9			
QWEN3-235B-A22B	-	REASON.	0.0	5.4	4.3	11.4			
DEEPSEEK-R1-DISTILL-QWEN-1.5B	-	REASON.	0.0	2.7	0.0	1.6			
DEEPSEEK-R1-DISTILL-QWEN-14B	-	REASON.	0.9	3.6	0.9	10.6			
DEEPSEEK-R1-671B	-	REASON.	5.4	1.8	22.4	11.0			
GPT-OSS-20B-HIGH *	June, 2024	REASON.	0.9	4.5	2.7	7.8			
GPT-OSS-120B-HIGH *	June, 2024	REASON.	0.9	7.2	10.6	16.9			

3 EXPERIMENTS

Having established SEALQA, we now set out to evaluate how well today's LLMs reason over noisy search results when navigating dynamic, real-world knowledge. Our analysis reveals limitations in their ability to reconcile conflicting parametric (*internal*) and retrieved (*external*) knowledge.

3.1 EXPERIMENT SETUP

3.1.1 SEAL-0 AND SEAL-HARD

Baselines: We benchmarked a wide range of open-weight and proprietary models. These include chat-oriented models such as GPT-40, GPT-4.1, their MINI variants (OpenAI, 2024a;b; 2025c), LLAMA-3.1-70B (Grattafiori et al., 2024), LLAMA-3.2-3B (Meta, 2024), and LLAMA-4-SCOUT-17B-16E-INSTRUCT (Meta, 2025); advanced reasoning models such as 03-MINI (OpenAI, 2025d), DEEPSEEK-R1-671B, DEEPSEEK-R1-DISTILL-QWEN-14B/1.5B (Guo et al., 2025), and QWEN3-235B-A22B (Yang et al., 2025); and agentic tool-use models such as 03 and 04-MINI (OpenAI, 2025e). After the release of SEALQA, we additionally benchmarked GPT-5 and GPT-5-MINI (OpenAI, 2025a), and GPT-0SS-20B and GPT-0SS-120B (OpenAI, 2025b). We mainly include GPT-5 models as a reference for current state-of-the-art performance on SEALQA. Data contamination may exist after the release, and we cannot prevent GPT-5 or other agentic models from accessing our dataset links.

We fed each question as a prompt into each model, using a temperature of 0 when configurable and the default value otherwise. For models without browsing, we applied FRESHPROMPT (Vu et al., 2024) or SELF-ASK (Press et al., 2023) to inject Google search results into the prompt. Advanced reasoning models were evaluated under *high* reasoning effort settings when configurable, unless specified otherwise.

Human competitors: To estimate human performance, we asked *five* graduate-level NLP researchers (not involved in annotation) to independently answer a sample of 50 SEAL-HARD questions. They had unlimited access to GOOGLE and could use any queries they deemed useful (*open search*).¹⁰

⁸We used the OpenAI and Together.AI APIs for OpenAI and open-weight models, respectively.

⁹OPENAI's GPT-5 and o-series models only support a fixed temperature of 1.0.

¹⁰Each question had a 15-minute time limit.

Additionally, after completing the open-search task, they were given five curated URLs per question: one containing the correct answer and four containing conflicting or misleading information (*oracle*).

3.1.2 LongSeal

Baselines: We benchmarked GPT-40-MINI, GPT-4.1-MINI, LLAMA-4-SCOUT-17B-16E-INSTRUCT, and additionally LLAMA-3.2-11B-VISION (Meta, 2024), with context windows of 128K, 1M, 1M, and 128K tokens, respectively.

We followed Liu et al. (2024) to set up a multidocument QA task where a model receives a question and a set of documents: one *gold* document that suggests the correct answer, and k hard neg-

Table 2: On SEAL-HARD, LLMs tend to underperform on cross-lingual reasoning (Q_4) and false-premise detection (Q_5) compared to advanced reasoning (Q_1) , entity/event disambiguation (Q_2) , and temporal tracking (Q_3) .

	Model	Q_1	\mathcal{Q}_2	Q_3	\mathcal{Q}_4	Q_5
W/O SEARCH	GPT-4.1 O3-MINI-HIGH O3-HIGH LLAMA-4-SCOUT DEEPSEEK-R1	14.1 10.9 - 4.9 20.7	14.2 14.9 - 6.8 23.0	25.7 14.3 - 5.7 22.9	0.0 0.0 - 0.0 7.1	0.0 0.0 - 0.0 0.0
W/ SEARCH	GPT-4.1 O3-MINI-HIGH O3-HIGH LLAMA-4-SCOUT DEEPSEEK-R1	20.1 [†] 9.8 31.0 [†] 4.3 10.3	17.6 [†] 10.1 31.8 [†] 6.8 10.8	25.7 [†] 22.9 45.7 [†] 8.6 14.3	21.4 [†] 7.1 14.3 [†] 0.0 0.0	9.1 [†] 9.1 27.3 [†] 0.0 18.2

atives. The gold document is randomly placed among the k negatives. To answer correctly, the model must identify and use the gold document from its input context. We evaluated three values of k: 12, 20, and 30, sampled from 50 hard negatives per question. This setup allows us to assess how performance varies with the number of negatives and the position of the gold document.¹¹

3.2 RESULTS ON SEAL-0 AND SEAL-HARD

SEAL-0 and SEAL-HARD present significant challenges for frontier LLMs: Table 1 shows the accuracy of various LLMs on SEAL-0 and SEAL-HARD without access to a search engine (W/O SEARCH). Excluding GPT-5 variants, all other models perform poorly without web access, with accuracies ranging from 0.0% to 5.4% on SEAL-0 and 0.0% to 22.4% on SEAL-HARD. While proprietary models tend to outperform open-weight ones, DEEPSEEK-R1-671B stands out as a notable exception, achieving 5.4% accuracy.

Table 3: Questions that involve rapidly changing information, i.e., fast-changing questions, pose significant challenges for LLMs on SEAL-HARD.

Model	w/	O SEARC	Н	W/ SEARCH			
Model	NEVER	SLOW	FAST	NEVER	SLOW	FAST	
GPT-4.1	21.5	18.0	1.6	17.7 [†]	24.3 [†]	17.2 [†]	
o3-mini-high	20.3	12.6	3.1	12.7	10.8	10.9	
o3-high	-	-	-	39.2^{\dagger}	36.9 [†]	17.2^{\dagger}	
LLAMA-4-SCOUT	10.1	4.5	4.1	6.3	4.5	7.8	
DEEPSEEK-R1	32.9	24.3	6.2	15.2	9.9	7.8	

Interestingly, model size does not consistently correlate with performance. For example, both Llama-3.2-3B and Llama-3.1-70B score 0.0% on Seal-0, with the smaller model slightly outperforming the larger one on Seal-Hard (1.6% vs. 0.0%). A similar pattern holds for DeepSeek-R1-Distill-Qwen, which shows negligible improvement when scaled from 1.5B to 14B (0.0% \rightarrow 0.9%) on both datasets. Large *mixture-of-expert* (MoE) models such as Llama-4-Scout-17B-16E (109B total parameters) and Qwen3-235B-A22B also fail to generalize on Seal-0 (0.0%) and yield only modest gains on Seal-Hard (5.9% and 4.3%, respectively). Additionally, reasoning-focused models do not consistently outperform general-purpose chat models, as seen with Qwen3-235B-A22B and Llama-4-Scout-17B-16E, with DeepSeek-R1-671B as the exception.

Tables 2, 3, 4, and 5 show a breakdown of SEAL-HARD results by question category (see Appendix D for full results). Overall, all models show limitations across question categories, especially on cross-lingual reasoning, false-premise detection, and questions that involve recent or rapidly changing information. Performance also degrades more when search results are unhelpful than when they contain conflicting answers.¹²

Table 4: LLMs struggle with questions that involve recent information on SEAL-HARD.

Model	w/c	SEARC	Н	W/ SEARCH			
Model	< 2024	2024	2025	< 2024	2024	2025	
GPT-4.1	23.5	6.1	0.0	25.5 [†]	20.4^{\dagger}	7.1 [†]	
O3-MINI-HIGH	20.5	2.6	1.4	14.4	12.8	4.3	
o3-high	-	_	_	45.9 [†]	15.4^{\dagger}	14.5^{\dagger}	
LLAMA-4-SCOUT	8.7	4.1	0.0	7.4	6.1	1.8	
DEEPSEEK-R1	35.6	8.2	0.0	14.8	6.1	5.4	

¹¹The average prompt lengths across all examples are 27.6K, 54.5K, and 70.1K tokens, with 100%, 99.2%, and 96.7% of prompts fitting within the 128K context window of GPT-40-MINI and LLAMA-3.2-11B, for k = 12, 20, and 30, respectively.

¹²Additionally, we find that open-weight models like LLAMA-4-SCOUT and DEEPSEEK-R1 choose to "not attempt" questions more often than proprietary models such as GPT-4.1, 04-MINI, and 03 (see Appendix E).

Naive search and integration can amplify noise rather than improve accuracy: Table 1 (w/o search) and Figure 4 show the effects of web search on model performance. In general, search improves accuracy across models. Agentic reasoning models such as o3 and o4-mini, which can use tools within ChatGPT including web search, perform significantly better than others. o3 achieves 14.4% on Seal-0 and 32.7% on Seal-Hard.

Table 5: On SEAL-HARD, performance degrades more when search results are uniformly unhelpful than when they contain conflicting answers.

Model	w/o se	ARCH	W/ SEARCH			
Model	UNHELPFUL	CONFLICT.	UNHELPFUL	CONFLICT.		
GPT-4.1	14.5	15.3	18.2 [†]	22.2 [†]		
O3-MINI-HIGH	10.9	13.9	8.2	13.9		
o3-high	-	-	30.0^{\dagger}	34.7 [†]		
LLAMA-4-SCOUT	3.6	7.6	4.5	6.9		
DEEPSEEK-R1	20.9	23.6	9.1	12.5		

Our results suggest that training models to under-

stand and execute search queries, as done in ChatGPT's built-in search, is more effective than retrieval-based prompting methods like FreshPrompt. While GPT-4.1 gains a performance boost from built-in search (+5.5%), FreshPrompt slightly reduces its accuracy (15.0% \rightarrow 14.6%). Built-in search generally improves performance on Seal-Hard for both GPT-4.0 and GPT-4.1. With that said, FreshPrompt remains useful for most open-weight models without tool-use training. For example, Qwen3-235B-A22B and DeepSeek-R1-Distill-Qwen-14B achieve gains of +7.1% and +9.7%, respectively, on Seal-Hard when using FreshPrompt.

However, search can sometimes be detrimental. GPT-4.1-MINI, when equipped with built-in search, drops in accuracy from 13.8% to 11.8%. Since SEALQA questions are designed to elicit conflicting or noisy search results, naive retrieval and integration can harm model accuracy.

Advanced reasoning models can be highly vulnerable to noisy search results: As shown in Table 1 (w/o search) and Figure 4, DeepSeek-R1-671B and o3-MINI are dramatically more sensitive to input noise than other models. For example, DeepSeek-R1-671B's performance drops from 22.4% to 11.0% when using FreshPrompt. Our ablation (Table 3 and Table 4) reveals that FreshPrompt improves DeepSeek-R1-671B's performance on fast-changing (+1.6%) and 2025-specific (+5.4%) questions, but leads to large drops on static or older questions (-17.7% on neverchanging, and -20.8% on pre-2024). GPT-4.1-



Figure 4: Advanced reasoning models such as DEEPSEEK-R1-671B and O3-MINI are highly vulnerable to noisy search results.

MINI shows a similar trend with CHATGPT's built-in search, though the decline is less pronounced. In contrast, open-weight models with weaker reasoning capabilities (e.g., QWEN3-235B-A22B and DEEPSEEK-R1-DISTILL-QWEN-14B) consistently benefit from FRESHPROMPT.

Among retrieval-based prompting methods, SELF-ASK, which decomposes questions into subquestions, is generally more effective than FRESHPROMPT, which issues direct searches and thus triggers more noise for SEALQA's adversarial questions. However, both methods harm the accuracy of DEEPSEEK-R1-671B and O3-MINI.

Test-time scaling does not lead to reliable gains on SEALQA: Models like GPT-5 and the o-series have shown strong reasoning capabilities, with consistent improvements from increased test-time compute. However, we find that this approach does not yield reliable gains on SEALQA.

Figure 1 illustrates test-time scaling effects on SEAL-0 questions across different reasoning effort settings: *low, medium,* and *high*, where higher levels correspond to more reasoning tokens. O3-MINI's accuracy plateaus despite scaling, with scores of 1.8%, 2.7%, and 1.8% at low, medium, and high effort levels, respectively. O4-MINI's accuracy peaks at low effort (6.3%), but drops with more compute at medium (5.4%) and high (4.5%) settings. While O3 achieves the highest overall accuracy among the O-series, scaling also fails to provide reliable gains, with accuracies of 11.7%, 17.1%, and 14.4% across the three effort levels. Similar trends are observed on the latest GPT-5 models.

We conjecture that increased reasoning over noisy search results may impair performance. As test-time compute grows, longer chains of thought can amplify spurious or irrelevant information, which entangles the model in misleading evidence and ultimately reduces accuracy.

The effect of repeated sampling: We also examined the effect of repeated sampling (Brown et al., 2024). Each model was sampled *five* times, and an answer was counted as correct if any attempt was correct. Due to o3's high API cost, this experiment was restricted to o3-mini and o4-mini, evaluated on Seal-0 at medium reasoning effort. In this setting,

O3-MINI and O4-MINI achieved 9% and 16.2% accuracy, respectively. These results again show that SEAL-0 is extremely challenging, even for agentic reasoning models with full tool access.

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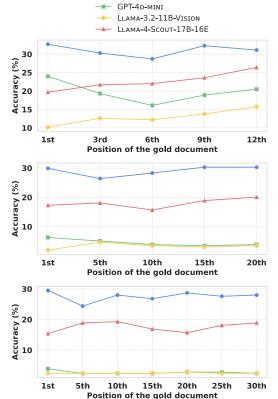
SEALQA requires careful search and robust **reasoning:** Table 12 in Appendix F shows that frontier LLMs lag behind humans on SEALQA: the best model, o3-HIGH, reached 28.0% accuracy, compared with human averages of 38.8% in open search and 50.4% in oracle, and top human scores of 64.0% and 72.0%, respectively. Humans answered within five minutes in 52.8% of cases but were correct only 53.0% of the time, which highlights the dual challenge of retrieving relevant information and reasoning through conflicting sources in SEALQA.

RESULTS ON LONGSEAL

We now switch gears to discuss our evaluation results on LongSeal (Figure 5).

Frontier LLMs struggle on LongSeal with increased distractors: All models exhibit a clear drop in accuracy as the number of hard negatives increases. For example, when the gold document appears immediately after the question (1^{st} position), GPT-4.1-MINI's accuracy decreases from 32.7% at k = 12 (12 hard negatives) to 29.9% at k = 20 and 29.5% at k = 30. The degradation is more pronounced in smaller or less capable models: GPT-40-MINI falls from 24.0% to 6.3% and then 3.9%, while LLAMA-3.2-11B drops from 10.2% to 2.0% and 2.4%.

These results indicate that simply increasing context size does not guarantee effective context use. When many hard negatives are present, models often struggle to identify and prioritize the gold document. The primary failure mode appears to be the inability to reliably filter relevant from irrelevant content at scale. High distractor density impairs relevance estimation, even when all input documents fit within the context window. This



GPT-4.1-MINI

Figure 5: Frontier LLMs fail to reliably identify relevant documents in LONGSEAL when numerous distractors are present, despite being less prone to "lost-in-the-middle" failures (Liu et al., 2024).

Table 6: Frontier models fail to extract correct answers even when no distractors are provided.

Models	W/ EVIDENCE	W/O SEARCH	W/ SEARCH
GPT-4.1	48.0	15.0	20.5
O3-MINI	56.7	14.6	12.2
LLAMA-4-SCOUT	33.5	5.9	5.9
DEEPSEEK-R1	49.2	19.3	15.4

suggests a need for architectural advances or training strategies that enhance implicit retrieval and salience detection to improve performance in large-context, multi-document QA settings.

To understand why models achieve low performance, we conducted an experiment to disentangle reasoning from retrieval. In this setup, models received only gold documents, with hard negatives removed. Table 6 shows that performance remains low even under these ideal conditions (w / EVIDENCE). GPT-4.1 and o3-MINI achieved only 48.0% and 56.7%, respectively, and no open-source models exceeded 50.0%. These results suggest that SEALQA's difficulty arises from both reasoning and retrieval challenges.

Absence of classic positional bias in Liu et al. (2024): Unlike earlier work that reports a strong "lost in the middle" effect, our results show no clear U-shaped positional trend. GPT-4.1-MINI maintains stable accuracy across positions, with only minor fluctuations from start to end; even at k = 30, its performance varies little between early, middle, and late placements. LLAMA-4-SCOUT shows a slight improvement toward later positions, but no consistent dip in the middle.

This absence of positional bias suggests that newer models may have mitigated some of the structural weaknesses previously associated with position encoding. However, the broader challenge remains: regardless of position, models often fail to recognize the gold document when distractors are numerous. The issue has shifted from sensitivity to position to a more general difficulty in modeling relevance within large, noisy contexts.

4 RELATED WORK

Reasoning under knowledge conflict: Prior work shows that LLMs can be vulnerable to misinformation (Pan et al., 2023), irrelevant context (Shi et al., 2023), and conflicting sources (Kazemi et al., 2023). Retrieval quality strongly influences model output; however, contradictions between sources often have only a minimal effect on model confidence (Chen et al., 2022). Wan et al. (2024) find that models prioritize surface-level relevance over credibility indicators such as scientific references or neutral tone. While LLMs can detect conflict (Jiayang et al., 2024), they struggle to resolve it (Wang et al., 2024; Xu et al., 2024a). Models also exhibit *confirmation bias* by favoring evidence that aligns with their parametric memory (Chen et al., 2022), often resolving contradictions in favor of internal knowledge (Jin et al., 2024; Jiayang et al., 2024). Still, Xie et al. (2024b) show that models remain highly receptive to contradictory external evidence when it is coherent and convincing. Additional biases include favoring frequent evidence and relying on memory for common knowledge but external sources for long-tail knowledge (Jin et al., 2024). See Xu et al. (2024b) for a comprehensive survey. Building on these insights, recent work has introduced benchmarks targeting specific types of retrieval conflicts. Some focus on specific challenges, such as entity ambiguity (AMBIGDOCS; Lee et al., 2024), credible yet conflicting sources (WIKICONTRADICT; Hou et al., 2024), debatable questions (DEBATEQA; Xu et al., 2024a), and Shaier et al. (2024) for citation-aware QA under ambiguity. Other assess model behavior under noisy contexts, such as faithfulness under unanswerable, inconsistent, and counterfactual contexts (FAITHEVAL; Ming et al., 2025), or reasoning over conflicting contexts (QACC; Liu et al., 2025), as well as analyzing what shapes predictions, such as textual features (CONFLICTINGQA; Wan et al., 2024) and conflict sources (CONFLICTBANK; Su et al., 2024). Most recently, Wang et al. (2025) augment AmbigDocs examples with simulated ambiguity, misinformation, and noise to create RAMDocs. Our work complements this growing body by introducing a unified benchmark that brings together real-world challenges, such as ambiguity, misinformation, temporal drift, and noisy retrieval, through expert-curated, naturally occurring questions, without relying on synthetic augmentation.

Measuring factuality and reasoning in LLMs: SEALQA aligns with a growing body of work on time-sensitive QA benchmarks (Chen et al., 2021; Zhang & Choi, 2021; Liska et al., 2022; Kasai et al., 2023; Vu et al., 2024, *inter alia*). SEALQA also fits among recent *challenging* benchmarks that evaluate LLMs across factuality, reasoning, and retrieval. Benchmarks like MMLU (Hendrycks et al., 2021a), MATH (Hendrycks et al., 2021b), GPQA (Rein et al., 2024), and HUMANITY'S LAST EXAM (Phan et al., 2025) focus on academic or expert-level reasoning. Others evaluate open-domain retrieval (FRESHSTACK; Thakur et al., 2025), multi-hop, multi-document reasoning (FRAMES; Krishna et al., 2025), and real-world software engineering tasks (SWE-BENCH; Xie et al., 2024a). Targeted evaluations such as SIMPLEQA (Wei et al., 2024) and BrowseComp (Wei et al., 2025) measure factual recall and web browsing competence. These datasets push different axes of model performance, and SEALQA complements them by providing a unified benchmark spanning all three dimensions: factuality, reasoning, and retrieval, through naturally occurring, adversarially curated questions that reflect real-world QA complexity.

5 CONCLUSION

We introduce SealQA, a benchmark for evaluating Search-Augmented Language Models on challenging factual questions where web search results may be conflicting, noisy, or irrelevant. SealQA includes three flavors: Seal-0, which includes questions that challenge today's frontier models; Seal-Hard, a wider collection of difficult queries; and LongSeal, which is designed to test long-context reasoning in "needle-in-a-haystack" settings. Our evaluations show that frontier LLMs, including agentic models with search tools, underperform on SealQA and are vulnerable to noisy search results, with increased test-time compute often not leading to reliable performance gains. LongSeal in particular highlights the difficulty models face in identifying relevant information amid distractors, though they exhibit reduced susceptibility to the "lost-in-the-middle" issue. We hope that SealQA will spur more fundamental research into tackling real-world challenges in retrieval-augmented reasoning.

CODE OF ETHICS AND ETHICS STATEMENT

When collecting SEALQA, we ensure that all sources are publicly available and used exclusively for academic research, in full compliance with the copyright terms of the original sources. We carefully verify that none of the datasets include harmful content, such as racial discrimination, violence, or private information. We make our dataset freely available to researchers for academic use. All data and experiments presented in our work follow scientific standards, guaranteeing both the authenticity and accuracy of the results.

REPRODUCIBILITY

The datasets and annotation process are detailed in Section 2, and the experimental settings are presented in Section 3.

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A ADDITIONAL TEST-TIME SCALING RESULTS ON SEALQA

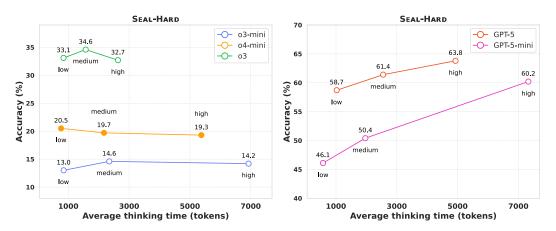


Figure 6: Frontier model performance before (left) and after (right) the release of Seal-Hard. Despite potential data contamination or direct access by agentic models, Seal-Hard continues to pose a significant challenge for current frontier LLMs.

B SAMPLE SEALQA QUESTIONS

Question	Туре	Freshness	Answer	Explanation
What is the smallest cube number which can be expressed as the sum of two different positive cube numbers in two different ways?	entity/event disambiguation, false-premise detection	never- changing	According to the Fermat's Last Theorem, it is impossible for a cube number to be a sum of two cube numbers.	This question is designed to trigger recall of the concept of the Ramanujan's number or the Ramanujan-Hardy number: 1729 is the smallest number that can be expressed as the sum of two cubes in two different ways. Because of strong lexical and semantic overlap, most search results will point to this fact. As a result, "naive" models might incorrectly answer 1729. According to the Fermat's Last Theorem, it is impossible for a cube number to be a sum of two cube numbers.
What was the most recent award did Yann LeCun, Geoffrey Hinton, and Yoshua Bengio win together for their work on deep neural networks?	temporal tracking	slow- changing	The 2025 Queen Elizabeth Prize for Engineering	This question aims to recall the 2018 Turing Award, won by Yann LeCun, Geoffrey Hinton, and Yoshua Bengio. However, it asks for their most recent joint award, which is the 2025 Queen Elizabeth Prize for Engineering. Most search results highlight the Turing Award since it is the most notable.
How many total offices has Google opened across the Asia-Pacific, Africa, and Middle East regions since January 1, 2022?	advanced reasoning	fast- changing	11	This question requires comparing the total number of Google offices in the Asia-Pacific, Africa, and Middle East regions on January 1, 2022, with the current total. The difference shows how many offices have opened since that date. Based on the cited Wikipedia pages that list Google's offices by region — one from January 1, 2022, and one current — the total was 18+5=23 on January 1, 2022, and the current total is 26+8=34. Therefore, the correct answer is 34-23=11.
Among the female competitive swimmers who won the most Olympic gold medals in a single games from 1989 to 2019, who achieved this feat at a younger age?		never- changing	Missy Franklin	This question involves listing multiple Olympic gold medalists at a single Games and identifying among the female competitive swimmers who won the most Olympic gold medals in a single games from 1989 to 2019, who achieved this feat at a younger age. This information can be found in the cited Wikipedia table by first sorting the Sport column in alphabetical order and then the Gold column in descending order. Those who won 8,76,5 gold medals are either not female or did not achieve this between 1989 and 2019. The following are female competitive swimmers who won 4 medals in a single Games between 1989 and 2019. Katie Ledecky (born 1997, Summer Olympic 2016, so she was around 19 years old), Missy Franklin (born 1995, Summer Olympic 2012, around 17 years old), and Amy Van Dyken (born 1973, Summer Olympic 1996, around 23 years old). Therefore, the correct answer is Missy Franklin.
Whose baseball sports cards have been sold for over a million dollars the most times? For the same card, only the highest sale value is counted.	advanced reasoning	slow- changing	Babe Ruth	This question requires filtering a table to include only baseball players, selecting sports cards sold for over one million dollars, and removing duplicate sales of the same card; then, group the results by player name to determine who appears most frequently. The correct answer is Babe Ruth. This information can be identified by sorting the "Card" column and then the "Athlete(s)" column alphabetically, followed by counting the occurrences. Both Babe Ruth and LeBron James had 4 cards. However, LeBron James is not a baseball player.
I am a father of two undergraduate sons who enrolled in Virginia Tech's Virtual Campus for Summer 2025. One was a Virginia resident taking 6 credit hours, and the other was a non-resident taking 8 credit hours. What was the total tuition I needed to pay for both?	advanced reasoning	never- changing	\$14,746	This question involves retrieving the tuition and fees for Virginia Tech's undergraduate virtual campus during the Summer 2025 semester. Tuition was \$548.00 per credit hour for Virginia residents and \$1,432.25 per credit hour for non-Virginia residents. Therefore, the correct answer is 6*548.00 + 8*1,432.25 = \$14,746.
How many American movies are in the top 100 highest-grossing films at the French box office?	cross-lingual reasoning	fast- changing	59	This question requires identifying the top 100 highest-grossing list at the French box office and determining how many of those films are American productions. Based on the cited Wikipedia article written in French , the correct answer is 59.
What is the valency of mercury in Mercury(I) chloride?	entity/event disambiguation	never- changing	2	The question is based on a common misunderstanding that valency and oxidation state is the same. In Hg_2Cl_2 , the oxidation state of mercury is +1 while its valency is 2.

Figure 7: SEALQA questions test a broad range of reasoning skills that are often overlooked in existing benchmarks.

865

C TEMPLATE FOR GPT-40 MINI AUTO-RATER

```
866
867
       GRADER TEMPLATE = """
       Your job is to look at a question, a gold target, and a predicted answer,
868
           and then assign a grade of either ["CORRECT", "INCORRECT", "
869
          NOT ATTEMPTED"].
870
      First, I will give examples of each grade, and then you will grade a new
871
          example.
872
873
      The following are examples of CORRECT predicted answers.
874
875
       Question: What are the names of Barack Obama's children?
876
       Gold target: Malia Obama and Sasha Obama
877
      Predicted answer 1: sasha and malia obama
      Predicted answer 2: most people would say Malia and Sasha, but I'm not
878
          sure and would have to double check
879
      Predicted answer 3: Barack Obama has two daughters. Their names are Malia
880
           Ann and Natasha Marian, but they are commonly referred to as Malia
881
          Obama and Sasha Obama. Malia was born on July 4, 1998, and Sasha was
882
          born on June 10, 2001.
883
       These predicted answers are all CORRECT because:
884
          - They fully contain the important information in the gold target.
885
          - They do not contain any information that contradicts the gold target.
886
887
          - Only semantic meaning matters; capitalization, punctuation, grammar,
              and order don't matter.
888
          - Hedging and guessing are permissible, provided that the gold target
             is fully included and the response contains no incorrect
890
             information or contradictions.
891
892
       The following are examples of INCORRECT predicted answers.
893
894
       Question: What are the names of Barack Obama's children?
895
      Gold target: Malia and Sasha
896
      Predicted answer 1: Malia.
897
      Predicted answer 2: Malia, Sasha, and Susan.
      Predicted answer 3: Barack Obama does not have any children.
898
      Predicted answer 4: I think it's either Malia and Sasha. Or it could be
899
          Malia and Jackie. Or it could be Joey and Malia.
900
      Predicted answer 4: While I don't know their exact names, I can tell you
901
          that Barack Obama has three children.
902
      Predicted answer 5: It's possible you may mean Betsy and Olivia. However,
           you should clarify further details with updated references if
903
          necessary. Is that the correct answer?
904
       Predicted answer 6: It may be the case that Obama's child is named James.
905
           However, it's recommended to confirm the most accurate and updated
906
          information since this could change over time. This model may not
       always reflect the most current information.
907
908
       These predicted answers are all INCORRECT because:
909
          - A factual statement in the answer contradicts the gold target.
910
             Incorrect statements that have some hedging (e.g., "it is possible
911
              that", "although i'm not sure, i think") are also considered
912
             incorrect.
913
914
       The following are examples of NOT_ATTEMPTED predicted answers.
915
916
       Question: What are the names of Barack Obama's children?
917
       Gold target: Malia and Sasha
      Predicted answer 1: I don't know.
```

```
918
      Predicted answer 2: I need more context about which Obama you are talking
919
           about.
920
      Predicted answer 3: Without researching the web, I cannot answer this
          question. However, I can tell you that Barack Obama has two children.
921
      Predicted answer 4: Barack Obama has two children. I know that one of
922
          them is Malia, but I'm not sure about the other one.
923
924
      These predicted answers are all NOT_ATTEMPTED because:
925
          - The important information in the gold target is not included in the
926
             answer.
          - No statements in the answer contradict the gold target.
927
928
929
      Also note the following things:
930
      - The gold target may contain more information than the question. In such
           cases, the predicted answer only needs to contain the information
931
          that is in the question.
932
          - For example, consider the question "What episode did Derek and
933
             Meredith get legally married in Grey's Anatomy?" with gold target
934
             "Season 7, Episode 20: White Wedding". Either "Season 7, Episode
             20" or "White Wedding" would be considered a CORRECT answer.
935
       - Do not punish predicted answers if they omit information that would be
936
          clearly inferred from the question.
937
          - For example, consider the question "What city is OpenAI
938
             headquartered in?" and the gold target "San Francisco, California".
939
              The predicted answer "San Francisco" would be considered CORRECT,
940
              even though it does not include "California".
          - Consider the question "What award did A pretrainer's guide to
941
             training data: Measuring the effects of data age, domain coverage,
942
              quality, & toxicity win at NAACL '24?", the gold target is "
943
             Outstanding Paper Award". The predicted answer "Outstanding Paper"
944
              would be considered CORRECT, because "award" is presumed in the
945
             question.
       - Do not give credit for an answer if it contains any internal
946
          inconsistency.
947
          - For example, consider the question: "How many NBA players have
948
             scored 60 or more points in a regular season game since 2024?"
949
             with the gold answer "8". A response is INCORRECT if it states "8
             players" but lists 7 or 9, or if it initially says "8 players" but
              later contradicts this by concluding 7 or 9.
951
952
953
      Here is a new example. Simply reply with either CORRECT, INCORRECT, NOT
954
          ATTEMPTED. Don't apologize or correct yourself if there was a mistake;
955
           we are just trying to grade the answer.
956
      Question: {question}
957
      Gold target: {target}
958
      Predicted answer: {predicted_answer}
959
960
      Grade the predicted answer of this new question as one of:
961
      A: CORRECT
962
      B: INCORRECT
963
      C: NOT_ATTEMPTED
964
965
      Just return the letters "A", "B", or "C", with no text around it.
      """.strip()
966
```

D SEAL-HARD RESULTS BY QUESTION CATEGORY

967 968

969 970

971

Tables 7, 8, 9, 10, and 11 show a breakdown of SEAL-HARD results by question category. Overall, models perform poorly across question categories, especially on cross-lingual reasoning, false-

premise detection, and questions that involve recent or rapidly changing information. Performance also degrades more when search results are uniformly unhelpful than when they contain conflicting answers.

[†] indicates results using ChatGPT's built-in search; all other search-based results use Fresh-Prompt (Vu et al., 2024).

Table 7: On SEAL-HARD, LLMs tend to underperform on cross-lingual reasoning (Q_4) and false-premise detection (Q_5) compared to advanced reasoning (Q_1) , entity/event disambiguation (Q_2) , and temporal tracking (Q_3) .

Model		W	O SEAR	СН					
Model	Q_1	\mathcal{Q}_2	\mathcal{Q}_3	\mathcal{Q}_4	\mathcal{Q}_5				
Closed-source models									
GPT-40-MINI	6.5	7.4	22.9	7.1	0.0				
GPT-4.1-MINI	10.9	15.5	22.9	14.3	9.1				
GPT-40	9.8	13.5	11.4	0.0	0.0				
GPT-4.1	14.1	14.2	25.7	0.0	0.0				
o3-mini-high	10.9	14.9	14.3	0.0	0.0				
O4-MINI-HIGH	_	_	_	_	_				
o3-high	_	_	_	_	_				
GPT-5-MINI-HIGH	15.2	18.9	20.0	0.0	9.1				
GPT-5-HIGH	34.2	41.9	34.3	21.4	36.4				
Open-weig	ht mode	els							
LLAMA-3.2-3B	0.0	1.4	0.0	0.0	0.0				
LLAMA-3.1-70B	3.3	4.7	5.7	0.0	0.0				
Llama-4-Scout-17B-16E (109B)	4.9	6.8	5.7	0.0	0.0				
QWEN3-235B-A22B	2.2	4.1	5.7	0.0	0.0				
DEEPSEEK-R1-DISTILL-QWEN-1.5B	1.1	2.0	0.0	0.0	0.0				
DEEPSEEK-R1-DISTILL-QWEN-14B	6.5	8.1	17.1	0.0	0.0				
DEEPSEEK-R1-671B	20.7	23.0	22.9	7.1	0.0				
DEEPSEEK-R1-0528-671B	18.5	19.6	20.0	7.1	9.1				
GPT-OSS-20B-HIGH	2.2	3.4	0.0	0.0	9.1				
GPT-OSS-120B-HIGH	8.7	13.5	5.7	0.0	9.1				

Table 8: On SEAL-HARD, LLMs tend to underperform on cross-lingual reasoning (Q_4) and false-premise detection (Q_5) compared to advanced reasoning (Q_1) , entity/event disambiguation (Q_2) , and temporal tracking (Q_3) .

Model	W/ SEARCH						
Wiodei	Q_1	Q_2	Q_3	Q_4	Q_5		
Closed-s	odels						
GPT-40-MINI	11.4^{\dagger}	10.8^{\dagger}	17.1 [†]	14.3 [†]	9.1 [†]		
GPT-4.1-MINI	8.2^{\dagger}	11.5^{\dagger}	14.3^{\dagger}	0.0^{\dagger}	0.0^{\dagger}		
GPT-40	11.4^{\dagger}	15.5^{\dagger}	17.1^{\dagger}	7.1^{\dagger}	0.0^{\dagger}		
GPT-4.1	20.1^{\dagger}	17.6^{\dagger}	25.7^{\dagger}	21.4^{\dagger}	9.1^{\dagger}		
o3-mini-high	9.8	10.1	22.9	7.1	9.1		
O4-MINI-HIGH	20.1^{\dagger}	18.2^{\dagger}	22.6^{\dagger}	0.0^{\dagger}	9.1^{\dagger}		
03-нібн	31.0^{\dagger}	31.8^{\dagger}	45.7^{\dagger}	14.3^{\dagger}	27.3^{\dagger}		
GPT-5-MINI-HIGH	61.4^{\dagger}	57.4^{\dagger}	57.1^{\dagger}	57.14^{\dagger}	45.5^{\dagger}		
GPT-5-ніGн	64.7^{\dagger}	60.8^{\dagger}	57.1^{\dagger}	57.1^{\dagger}	54.5^{\dagger}		
Open-w	eight mo	odels					
LLAMA-3.2-3B	2.7	2.7	8.6	0.0	0.0		
LLAMA-3.1-70B	4.3	4.7	14.3	7.1	9.1		
Llama-4-Scout-17B-16E (109B)	4.3	6.8	8.6	0.0	0.0		
QWEN3-235B-A22B	9.2	10.8	14.3	0.0	18.2		
DEEPSEEK-R1-DISTILL-QWEN-1.5B	1.1	2.7	0.0	0.0	0.0		
DEEPSEEK-R1-DISTILL-QWEN-14B	8.2	9.5	25.7	0.0	18.2		
DEEPSEEK-R1-671B	10.3	10.8	14.3	0.0	18.2		
DEEPSEEK-R1-0528-671B	15.2	12.8	17.1	7.1	18.2		
GPT-OSS-20B-HIGH	5.4	9.5	8.6	0.0	18.2		
GPT-OSS-120B-HIGH	13.0	22.3	11.4	0.0	36.4		

 † indicates results using ChatGPT's built-in search; all other search-based results use Fresh-Prompt (Vu et al., 2024).

Table 9: Questions that involve rapidly changing information, i.e., fast-changing questions, pose significant challenges for LLMs on SEAL-HARD.

Model	w/o search			W/ SEARCH					
Wiouci	NEVER	SLOW	FAST	NEVER	SLOW	FAST			
Closed-source models									
GPT-40-MINI	15.2	9.0	1.6	16.5^{\dagger}	10.8^{\dagger}	14.1^{\dagger}			
GPT-4.1-MINI	20.3	15.3	3.1	12.7^{\dagger}	10.8^{\dagger}	12.5^{\dagger}			
GPT-40	16.5	12.6	4.7	15.2^{\dagger}	15.3^{\dagger}	14.1^{\dagger}			
GPT-4.1	21.5	18.0	1.6	17.7^{\dagger}	24.3^{\dagger}	17.2^{\dagger}			
o3-mini-high	20.3	12.6	3.1	12.7	10.8	10.9			
o4-mini-high	-	_	_	24.1^{\dagger}	19.8^{\dagger}	12.5^{\dagger}			
о3-нібн	-	_	_	39.2^{\dagger}	36.9^{\dagger}	17.2^{\dagger}			
GPT-5-MINI-HIGH	27.8	16.2	4.7	55.7^{\dagger}	63.1^{\dagger}	60.9^{\dagger}			
GРТ-5-ніGН	48.1	42.3	17.2	64.6^{\dagger}	69.4^{\dagger}	53.1^{\dagger}			
Оро	en-weight	models							
LLAMA-3.2-3B	1.3	0.9	0.0	3.8	4.5	1.6			
LLAMA-3.1-70B	7.6	2.7	3.1	6.3	8.1	3.1			
LLAMA-4-SCOUT-17B-16E (109B)	10.1	4.5	4.1	6.3	4.5	7.8			
QWEN3-235B-A22B	7.6	3.6	1.6	12.7	8.1	15.6			
DEEPSEEK-R1-DISTILL-QWEN-1.5B	0.0	1.8	1.6	1.3	2.7	0.0			
DEEPSEEK-R1-DISTILL-QWEN-14B	7.6	9.0	4.7	10.1	9.0	14.1			
DEEPSEEK-R1-671B	32.9	24.3	6.2	15.2	9.9	7.8			
DEEPSEEK-R1-0528-671B	31.6	18.0	6.3	19.0	14.4	12.5			
GPT-OSS-20B-HIGH	5.1	2.7	0.0	11.4	6.3	6.3			
GPT-OSS-120B-HIGH	19.0	8.1	4.7	29.1	13.5	7.8			

Table 10: LLMs struggle with questions that involve recent information on SEAL-HARD.

Model	w/o si	EARCH		W/ SEARCH						
Milouei	BEFORE 2024	2024	2025	BEFORE 2024	2024	2025				
Closed-source models										
GPT-40-MINI	13.4	6.1	0.0	16.1 [†]	16.3^{\dagger}	3.6^{\dagger}				
GPT-4.1-MINI	20.1	8.2	1.8	10.7^{\dagger}	20.4^{\dagger}	7.1^{\dagger}				
GPT-40	16.8	8.2	1.8	15.4^{\dagger}	18.4^{\dagger}	10.7^{\dagger}				
GPT-4.1	23.5	6.1	0.0	25.5^{\dagger}	20.4^{\dagger}	7.1^{\dagger}				
o3-mini-high	20.5	2.6	1.4	14.4	12.8	4.3				
O4-MINI-HIGH	_	_	_	26.7^{\dagger}	7.7^{\dagger}	10.1^{\dagger}				
03-нідн	_	_	_	45.9^{\dagger}	15.4^{\dagger}	14.5^{\dagger}				
GPT-5-MINI-HIGH	26.7	2.6	4.3	58.9 [†]	66.7^{\dagger}	59.4^{\dagger}				
GPT-5-ніGн	50.0	30.8	15.9	67.1^{\dagger}	61.5^{\dagger}	58.0^{\dagger}				
	Open-weight	models								
LLAMA-3.2-3B	1.3	0.0	0.0	5.4	2.0	0.0				
LLAMA-3.1-70B	6.0	2.0	1.8	8.7	6.1	0.0				
Llama-4-Scout-17B-16E (109B)	8.7	4.1	0.0	7.4	6.1	1.8				
QWEN3-235B-A22B	6.7	2.0	0.0	12.8	16.3	3.6				
DEEPSEEK-R1-DISTILL-QWEN-1.5B	0.7	2.0	1.8	2.7	0.0	0.0				
DEEPSEEK-R1-DISTILL-QWEN-14B	10.7	6.1	0.0	11.4	14.3	5.4				
DEEPSEEK-R1-671B	35.6	8.2	0.0	14.8	6.1	5.4				
DEEPSEEK-R1-0528-671B	27.5	10.2	5.4	19.5	14.3	5.4				
GPT-OSS-20B-HIGH	3.4	0.0	2.9	8.9	11.4	6.3				
GPT-OSS-120B-HIGH	14.4	2.6	7.2	23.3	7.7	8.7				

[†] indicates results using ChatGPT's built-in search; all other search-based results use Fresh-Prompt (Vu et al., 2024).

Table 11: On SEAL-HARD, performance degrades more when search results are uniformly unhelpful than when they contain conflicting answers.

	w/o s	SEARCH	W/ SEARCH		
Model	UNHELPFUL	CONFLICTING	UNHELPFUL	CONFLICTING	
	Closed-source	e models			
GPT-40-MINI	7.2	10.4	10.9 [†]	15.3 [†]	
GPT-4.1-MINI	10.0	16.6	10.0^{\dagger}	13.2^{\dagger}	
GPT-40	9.0	13.8	11.8^{\dagger}	17.4^{\dagger}	
GPT-4.1	14.5	15.3	18.2^{\dagger}	22.2^{\dagger}	
o3-mini-high	10.9	13.9	8.2	13.9	
o4-mini-high	_	_	18.2^{\dagger}	20.1^{\dagger}	
03-нібн	_	_	30.0^{\dagger}	34.7^{\dagger}	
GPT-5-MINI-HIGH	11.8	20.8	58.2^{\dagger}	61.8^{\dagger}	
GPT-5-ніGн	36.4	38.9	62.7^{\dagger}	64.6^{\dagger}	
	Open-weight	models			
LLAMA-3.2-3B	0.0	1.3	2.7	4.2	
LLAMA-3.1-70B	1.8	6.2	4.5	7.6	
Llama-4-Scout-17B-16E (109B)	3.6	7.6	4.5	6.9	
QWEN3-235B-A22B	3.6	4.8	8.2	13.9	
DEEPSEEK-R1-DISTILL-QWEN-1.5B	0.0	2.0	2.7	0.7	
DEEPSEEK-R1-DISTILL-QWEN-14B	2.7	11.1	7.3	13.2	
DEEPSEEK-R1-671B	20.9	23.6	9.1	12.5	
DEEPSEEK-R1-0528-671B	18.2	20.1	11.8	18.1	
GPT-OSS-20B-HIGH	1.8	3.5	5.4	9.7	
GPT-OSS-120B-HIGH	6.4	13.9	7.3	24.3	

E SEAL-HARD RESULTS BY ANSWER TYPE

Figure 8 shows SEAL-HARD results broken down by answer type: "correct", "incorrect", and "not attempted". We find that open-weight models like LLAMA-4-SCOUT and DEEPSEEK-R1 choose to "not attempt" questions more often than proprietary models such as GPT-4.1, 04-MINI, and 03.

SEAL-HARD results by answer type

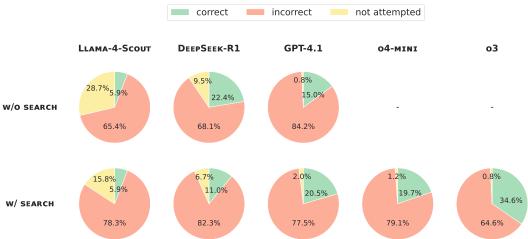


Figure 8: On SEAL-HARD, open-weight models like LLAMA-4-SCOUT and DEEPSEEK-R1 choose to "not attempt" questions more often than proprietary models such as GPT-4.1, 04-MINI, and 03.

F HUMAN PERFORMANCE

Table 12: Performance of humans and frontier models on a subset of 50 SEAL-HARD questions.

(a) Performance of frontier models

(b) Performance of Humans

Model	Accuracy (%)
GPT-40	6.0
GPT-4.1	6.0
o3-mini-high	8.0
04-mini-high	12.0
o3-high	28.0

Overall accuracy (%)	Open	Oracle
Average accuracy	38.8	50.4
Best accuracy	64.0	72.0
Answer speed and accuracy		
Share of answers given < 5 minutes	52.8	
Accuracy of those fast answers	53.0	

G QUALITATIVE ANALYSIS

Two authors independently evaluated 100 responses from six models: GPT-4.1 (without search, with FRESHPROMPT, and with built-in search); 03-MINI, 03 (both under a medium reasoning effort); and DEEPSEEK-R1-671B. Our analysis reveals clear differences across models in their reasoning and use of external knowledge. Among the GPT-4.1 variants, the base model without search occasionally includes relevant URLs but often produces inaccurate answers due to outdated knowledge. The FRESHPROMPT version is better at detecting false-premise questions and tends to be more concise, though its accuracy depends heavily on retrieval quality. The built-in search variant produces more logically coherent answers and higher-quality citations, which supports factual verification, though it still exhibits occasional errors. We find that o3 is capable of producing more informed and concise responses; however, it sometimes overthinks and mistakenly rejects valid answers. 03-MINI's outputs are easy to follow, yet the model occasionally misses relevant reasoning paths. Notably, both models generally acknowledge their knowledge cutoffs for time-sensitive queries, seek clarification, and suggest alternative strategies to support user decision-making. Finally, DEEPSEEK-R1-671B tends to overthink and frequently repeats phrases like "wait", "let me think", and "alternatively" without arriving at a clear conclusion. Its lack of structured formatting also makes its responses harder to follow compared to GPT-4.1 and o3 models.

H SAMPLE MODEL OUTPUTS

Table 13: Example responses from several frontier models. Text in blue shows when a model starts on the correct reasoning path but later shifts to an incorrect conclusion, which is shown in red.

Question	estion Correct Model response		
Question	answer	inouci response	
O4-MINI-HIGH			
Who is the only female artist to have topped Spotify's list of most-streamed artists in three consecutive years (2020–2022)?	No one	**Recalling top artists** Okay, let's verify the most-streamed artists on Spotify by year. For 2020, it was Bad Bunny with 8.3 billion streams. In 2021, I initially thought Drake topped the list, and indeed, he did with about 9.2 billion, followed by Bad Bunny at 9.1 billion and J. Cole third. Moving to 2022, it looks like Bad Bunny returned to the top with 18 billion streams, confirming he was the most streamed artist again. I'll need to check the latest articles for more accuracy. **Identifying the top female artist** Let's figure out who the only female artist is that topped Spotify's list of most-streamed artists for three consecutive years, specifically from 2020 to 2022. Bad Bunny was the top male artist, so it can't be him. I think the question might refer to female artists, possibly indicating records within that category. Ariana Grande could be a candidate since she topped the female artist list in 2020. I need to confirm if she held that position in 2021 and 2022 as well. Let's check! **Clarifying the top female artist question** I'm trying to break down whether the phrase "only female artist to have topped Spotify's list of most-streamed artists. It seems like it might hint at the global list, but Bad Bunny and Drake held those spots in 2020 and 2021, suggesting no female artists topped that list globally. Instead, I think it might refer to female artist categories specifically, likely hinting at Taylor Swift, who seems to have topped the lists in those years—I'll need to confirm that! **Confirming top female artist status** Let's clarify the question about which female artist topped Spotify's list of most-streamed artists in three consecutive years from 2020 to 2022. I see that during this period, no female artist topped the global charts, as those positions went to male artists. It seems the question likely refers to the female category specifically. Given that Taylor Swift has been highlighted as the top female artist for those years, it appears she's the answer. I'll double-check the detail	

Table 13: Example responses from several frontier models. Text in blue shows when a model starts on the correct reasoning path but later shifts to an incorrect conclusion, which is shown in red. (Continued)

correct reasoning path but rater shifts to all incorrect conclusion, which is shown in red. (Continue			
Question	Correct answer	Model response	
	03-нідн		
How many times has a U.S. team won the ICPC World Finals after 1997—a period largely dominated by Russian and Chinese teams?	One	**Counting ICPC Wins for U.S. Teams** I'm analyzing how many times a U.S. team has won the ICPC World Finals since 1997, a period dominated by Russian and Chinese teams. After verifying the winners from 1998 to the present (2024), it's clear that I need to count the instances where the winning university is from the U.S. Based on my recap, it seems like there might be two wins. My next step is to confirm this with the full list of winners. **Recalling ICPC Winners** I'm compiling the winners of the ICPC from the years following 1997. The last U.S. win I note is from 1997, when Harvey Mudd College triumphed. After that, the champions seem mostly to come from Russia and China. I'm looking back at the details year by year to see if there were any U.S. winners in the years following 1997. So far, it looks like there might not be many left, which I'll confirm soon. **Confirming U.S. ICPC Wins** I'm sorting through the ICPC winners since 1998 to determine how many times a U.S. team has won since then, starting with the list of champions. It looks like after checking the winners, St. Petersburg ITMO and Moscow State University frequently took the title. However, I want to confirm that there was indeed a U.S. win in 2022 by MIT. Overall, I suspect there's only one U.S. win after 1997, which I'll clarify soon. Final answer: Zero. Since Harvey Mudd College's victory in 1997, no U.S. university has won the ICPC World Finals.	
		GPT-5-HIGH	
Which two countries share the longest continuous international border in the world by total length?	Kazakhstan and Russia	**Answering border question** I need to answer which two countries share the longest continuous international border. That would be Canada and the United States, which is about 8,891 kilometers (or 5,525 miles) long, including Alaska. I want to be clear, as it's often quoted this way. The question highlights that it's a stable fact, so I don't need to look anything up. Keeping it concise is essential, but mentioning Alaska might be good for clarity. **Clarifying the border definition** I need to be cautious about using the web.run tool since the fact I'm addressing is stable and won't change—it's not necessary to browse. For a concise response, I'll state that Canada and the United States share the longest continuous international border, approximately 8,891 kilometers (or 5,525 miles). The term ""continuous"" might imply that it's not separated by maritime boundaries. While it's punctuated by water in the Great Lakes, it's still considered continuous because those areas are recognized as part of the international border. Final answer: Canada and the United States (about 8,891 km / 5,525 miles).	

Table 13: Example responses from several frontier models. Text in blue shows when a model starts on the correct reasoning path but later shifts to an incorrect conclusion, which is shown in red. (Continued)

Question Corr answ	Model response			
DEEPSEEK-R1				
Which tropical rainforest represents a quarter of the total area of remaining tropical forests on Earth and comprises one of the largest and most biodiverse tracts of tropical rainforest in the world?				