

***ExecRubrics*: Executable Tool-Augmented Rubrics for Verifiable and Efficient Long-Form Evaluation**

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Abstract

Rubrics aim to make language-model evaluation transparent by decomposing response quality into interpretable criteria. However, natural-language rubrics are often ambiguous, require black-box LLM judges, and typically assume criteria aggregate independently through linear weighted sums, limiting their ability to capture dependencies, alternatives, penalties, and override conditions. We propose *ExecRubrics*, a framework for representing rubrics as compact executable programs. *ExecRubrics* encodes evaluation logic as verifiable Python scoring functions, giving natural-language rubric intent an operational semantics: a fixed decision procedure that can be inspected, executed, and edited. On three long-form response benchmarks—HealthBench, HelpSteer, and ArgQuality—we show that *ExecRubrics* can substitute for expensive black-box judges in ranking preferred over dispreferred responses, matching or improving NL rubric baselines with best preference accuracies of 52.9%, 75.3%, and 91.5%, respectively, while reducing evaluation latency by a large margin. We show that incorporating external logic and resources from text processing libraries such as NLTK and spaCy can further improve preference accuracy. Our results suggest a novel way of looking at evaluation, by offering a faster, more explainable and less ambiguous alternative to black-box rubric evaluation, particularly in high-stakes domains such as healthcare and banking where precision and auditability are critical.

1 Introduction

Large Language Models (LLMs) are increasingly evaluated and trained with automated graders, such as LLM-as-judge systems that output scalar scores or preferences. Although convenient, these judgments are opaque: they rarely explain which requirements were missed or how a system should improve. This is especially problematic in high-stakes domains such as health (Hager et al., 2024;

Asan et al., 2020; Sivasothy et al., 2026) where precision is critical or in evaluating long-horizon workflows where evaluation should account for multiple intermediate deliverables (Sun et al., 2026; Chen et al., 2026; Phan et al., 2025; Kapoor et al., 2026). Rubric-based evaluation addresses this by decomposing response quality into explicit natural-language criteria (Arora et al., 2025; Dhole et al., 2025b).

Natural-language rubrics, however, still leave the operational semantics of evaluation underspecified as generic and abstract criteria often are less effective for downstream evaluation (Popham, 1997; Li and Lindsey, 2015). A rubric item such as “appropriately recommends urgent care” or a corpus level item such as “instruction following ability” is readable, but is vague and ambiguous. In practice, each item often requires a separate human or a black-box LLM judge to decide whether the criterion is satisfied. This reintroduces subjectivity at the level of each atomic criterion, makes the final score sensitive to the judge model, provides limited operational explainability due to dependency on a black-box LLM and makes it difficult to forecast the change when the rubric needs editing.

It also encourages flat weighted checklists, even though evaluation logic may involve prerequisites, alternatives, penalties, and overrides. For example, in a medical query mentioning a penicillin allergy, an executable rubric can activate an allergy-specific branch, reward non-penicillin alternatives, and penalize uncaveated amoxicillin recommendations.

In that regard, we propose *ExecRubrics*: a representation that compiles rubric intent into small symbolic scoring programs. Each program defines the checks, branches, penalties, normalization, and tool calls used to score a candidate response. Since modern LLMs are strong code generators, we study whether they can approximate human-written natural-language rubrics as executable evaluators.

Such executable rubrics can be made more

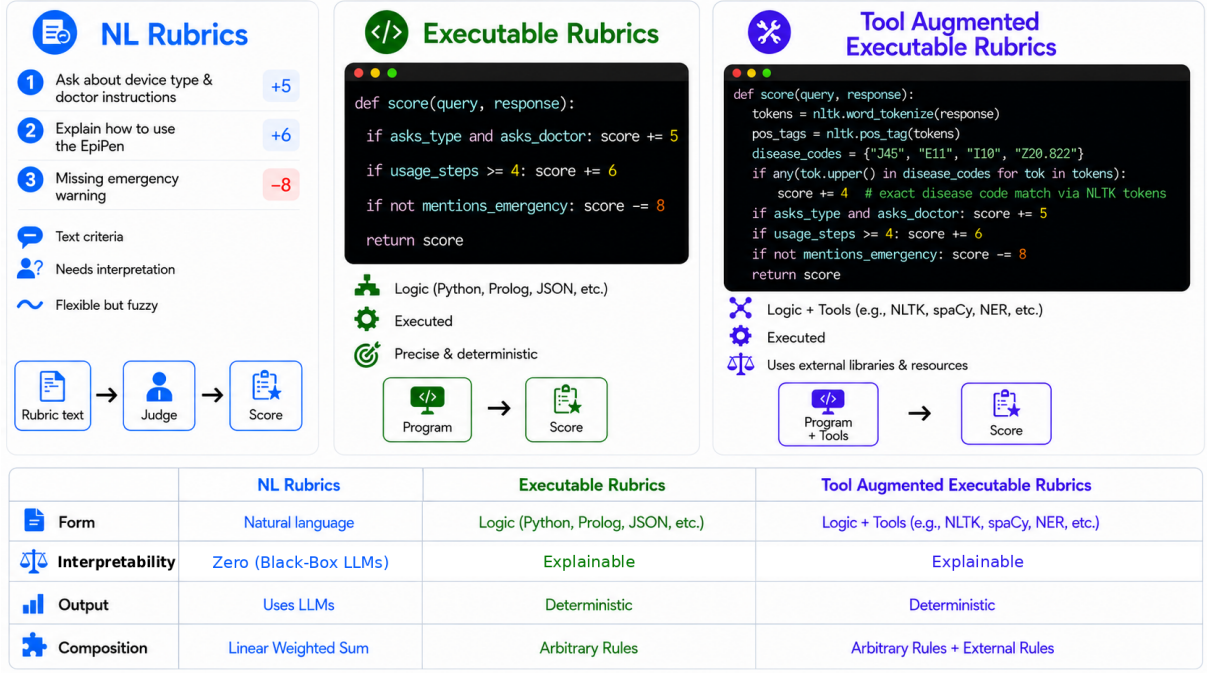


Figure 1: Natural language rubrics can be ambiguous and require a judge to compute criterion satisfiability. Executable rubrics are deterministic and verifiable mitigating the need of the judge.

expressive by composing deterministic NLP tools—tokenizers, lexicons, entity recognizers, negation detectors, readability, and n-gram metrics—as transparent primitives for atomic checks.

Specifically, we are interested in answering the research question: *Can LLMs generate executable rubrics that deterministically distinguish high-quality responses from low-quality responses as effectively as natural-language rubrics?*

In that regard, our contributions are as follows:

- We introduce **ExecRubrics** as an explicit rule-based representation to capture complex layers of expressivity and explainability for response evaluation as shown in Figure 1.
- We then demonstrate how Python-based **ExecRubrics** can be generated from natural language rubrics. Across HealthBench, ArgQuality, and HelpSteer, we evaluate whether executable rubrics can serve as a judge-free intermediate representation for preference evaluation. We find that generated Python rubrics often match or exceed natural-language rubric judging while making the scoring logic inspectable, deterministic, and modifiable.
- We further show how allowing these rubrics to exploit logic through external text processing tools improves their preference ability further by providing more expressive power.

2 Related Work

LLM-as-judge and fine-grained evaluation: LLMs are increasingly used as automated evaluators, producing scalar scores, preferences, or structured ratings (Dhole et al., 2025b; Dhole and Agichtein, 2024; Dhole et al., 2025a). Frameworks such as G-Eval show that prompted LLM judges can correlate with human judgments (Liu et al., 2023), but scalar judgments offer limited diagnostic feedback. Fine-grained evaluation addresses this by decomposing response quality into smaller criteria (Li et al., 2026; Farzi and Dietz, 2025): For instance, FLASK evaluates instance-specific alignment skills (Ye et al., 2024), while FActScore variants decompose long-form summaries into atomic claims or nuggets (Min et al., 2023; Chung et al., 2026; Jeong et al., 2025). These works motivate rubric-style evaluation, but the resulting units are still typically interpreted through long natural language descriptions which are often complex.

Rubric-based and adaptive evaluation: Rubric-based benchmarks make evaluation more transparent by exposing the criteria used to score responses. HealthBench uses physician-written, query-specific criteria with point values (Arora et al., 2025; Hicks et al., 2026; Cook et al., 2024); and ProfBench (Wang et al., 2025) and PRBench (Akyürek et al., 2025) use expert-

authored weighted rubrics in professional domains. Recent work also makes rubrics more scalable and adaptive: RUBICON generates rubrics for domain-specific conversations (Biyani et al., 2024), Health-SCORE selects relevant healthcare rubric items for each prompt (Mallinar et al., 2026), and RubricRAG retrieves related examples to generate query-specific rubrics (Dhole and Agichtein, 2026). However, these systems still largely represent rubrics as a weighted linear sum of natural-language checklist items whose satisfaction must be judged by a human or an LLM.

Limitations of natural-language rubrics:

Prior assessment work shows that rubrics are not automatically reliable or valid: they require clear, appropriately granularity (Dhole and Agichtein, 2026; Fensore et al., 2026) and, often calibration or exemplars (Li and Lindsey, 2015). Vague criteria can lead raters to interpret rubrics inconsistently or rely on holistic impressions (Popham, 1997). This limitation is especially relevant for LLM evaluation, where criteria such as “does not overstate certainty” or “appropriately recommends urgent care” remain operationally underspecified and require another judge to decide whether they are satisfied.

Interpretable symbolic approximations of neural models; A parallel line of work uses symbolic representations to approximate black-box neural models to allow expressing explicit rules, prior knowledge, and controllable constraints (Wang et al., 2021). This includes distilling compact symbolic expressions like circuit discovery (Rai et al., 2026) from trained models (Cranmer et al., 2020) and translating predictions into rules or reasoning trails (Armgaan et al., 2024; Rorseth et al., 2026). Unlike work focused on model internals, factual associations, or causal structure, we make the evaluation rubric itself executable, inspectable, and human-modifiable. Some works have argued for structured, test-like evaluation for response evaluation, for instance through behavioral tests (Ribeiro et al., 2020), graph-based rubric representations for automatic short-answer grading (Condor et al., 2022) and rule-based rewards (Mu et al., 2024). Our work also follows this motivation but is focused on downstream evaluation as well: instead of using natural-language criteria interpreted by a judge, *ExecRubrics* represents rubrics as small executable programs. This allows deterministic scoring logic, explicit dependencies, alternative sat-

isfaction paths, penalties, and safety-critical overrides while preserving the interpretability goal of rubric-based evaluation.

3 Rubric-Based Evaluation

We consider the setting where an evaluator must choose a preferred response y^+ over a dispreferred response y^- for an input query x through rubric criteria. Let R denote rubric system, e.g., a set of rubric items or criteria and let $E_R(y|x)$ denote an evaluation score assigned to a candidate response y for a query x under the rubric system R . A rubric-based evaluator is effective when it assigns a higher score to the preferred response. One measures the effectiveness under a rubric system by measuring the preference accuracy across a large number of query and preference pairs $\mathcal{D}$.

$$\text{Acc}_R = \frac{1}{|\mathcal{D}|} \sum_{(x, y^+, y^-) \in \mathcal{D}} \mathbf{1}[E_R(y^+|x) > E_R(y^-|x)]$$

Rubric-based evaluation therefore reduces preference prediction to criterion-guided scoring: the rubric specifies what properties a good answer should satisfy, and the evaluator computes a score based on whether the candidate response satisfies those properties.

3.1 Natural Language Rubrics

In rubric-based evaluations, the rubric system represented rubric criteria as a list of (weighted) items:

$$R = \{(r_1, p_1), (r_2, p_2), \dots, (r_n, p_n)\}$$

where r_i is a textual description of the i -th rubric criterion and $p_i \in \mathbb{R}$ is the number of points assigned to each criterion. Positive points reward desirable properties, while negative points penalize unsafe, incorrect, or otherwise undesirable properties.

Because each rubric criterion is written in long descriptive natural language, its satisfaction is not directly computable. A separate judge model M is therefore used to determine whether response y satisfies criterion r_i for query x :

$$M(x, y, r_i) \in \{0, 1\}$$

The final rubric score is then computed as a weighted sum of satisfied criteria, normalized by the total positive points:

$$E_R(y|x) = \frac{\sum_{i=1}^n p_i \cdot \mathbb{1}[M(x, y, r_i) = 1]}{\sum_{i=1}^n p_i \cdot \mathbb{1}[p_i > 0]}$$

This formulation makes evaluation more interpretable than a single scalar judge score because individual criteria can be inspected. However, the semantics of each criterion are still mediated by M , and the aggregation assumes that criteria contribute independently and linearly to the final score.

3.2 Executable Rubrics

We define an executable rubric as a symbolic scoring program that evaluates the candidate response based on any arbitrary function f_{r_i} that approximates a rubric criteria r_i into explicit rules. Specifically, an executable rubric replaces judge-mediated criterion satisfaction with a scoring function f_{r_i} that encodes explicit rules and may call deterministic tools for atomic text checks or arbitrary logic:

Unlike natural-language rubrics, executable rubrics make the scoring procedure explicit. They can encode conditional logic, prerequisites, alternative satisfaction paths, penalties, and override rules directly in some logical form e.g., Python code.

$$E_R(y|x) = \frac{\sum_{i=1}^n p_i \cdot f_{r_i}(x, y)}{\sum_{i=1}^n p_i \cdot \mathbb{1}[p_i > 0]}.$$

where f_{r_i} is an executable scoring function approximated from rubric r_i .

4 Experimental Setup

We now describe our experimental setup where we compare the effectiveness of human written rubrics and the corresponding translated executable rubrics, with and without external logic.

Benchmarks: We evaluate preference accuracy over three datasets that provide both rubric information and preference-style supervision. First, on **HealthBench** (Arora et al., 2025), we treat the physician-authored completions as the positive responses and use negative responses from RubriC-RAG (Dhole and Agichtein, 2026), which are generated by conditioning on mismatched rubrics. We also evaluate on two long-form preference benchmarks, **HelpSteer** (Wang et al., 2024) and **ArgQuality** (Gienapp et al., 2020). Our primary metric is **Preference Accuracy**: the fraction of queries for which the positive response is preferred over the negative response.

Rubric Generation Methods:

1. **NL Rubrics:** We first compute preference accuracies using human-written rubric criteria. Each benchmark has 5 to 14 corpus-level criteria like cogency, emotional appeal,

instruction following, etc., shown in Table 2. We use single sentence definitions for each of them. Qwen3-30B-Instruct-A3B (Yang et al., 2025) is used for predicting criterion satisfaction.¹

2. **Executable Rubric Variants:** We evaluate three families of executable rubrics by generating them from their natural language counterparts.

(i) **Executable Rubrics:** the model directly converts natural-language rubrics into Python scoring functions. Each rubric criterion (e.g., cogency, coherence, etc.) is translated to one scoring function, and the sum of the scores is used for evaluating (query, response) pairs (i.e. we use $p_i = 1$ for all rubric criteria). The prompts used for generating the rubrics are shown in Appendix Figure 4 (ii) **Executable Rubrics with Popular tools:** the model generates a Python scoring function with access to two widely used NLP libraries, **NLTK** (Bird, 2006) and **spaCy** (Honnibal et al., 2020). (iii) **Executable Rubrics with Deterministic Tools:** the model generates a Python scoring function that can call a wider range of different deterministic text processing libraries. For **ArgQuality**, and **HealthBench**, we use few-shot prompts by constructing 3 executable functions for 3 rubric criteria from HelpSteer. For **HelpSteer**, we construct a zero-shot prompt. We evaluate 3 frontier LLMs, viz., GPT 5.5 (OpenAI, 2026), Claude Sonnet 4.6 (Anthropic, 2026), and Gemini 3.5 Flash (Google, 2026).

3. **Black-Box Agentic Evaluation:** We also include a no rubric agentic baseline using GPT 5.5. Given the long context length of 1M, we feed a single query file to the chat, and prompt it to generate preferred response for each row of the file.

Tool Augmentation: We augment rubric generation with helper functions built on top of existing text-processing libraries and deterministic analyzers (shown in Appendix A), and expose them directly in the prompts so the model sees their signatures, inputs, and outputs. For popular-library augmentation, this includes functions for tokenization, lemmatization, entity extraction, phrase matching, profanity checks, negation detection, and lexical frequency statistics. For deterministic-tool augmentation, we expose higher-level checks such as

¹We use NVIDIA H200 for NL rubric experiments. Different choices of NL judges may result in different performances.

Rubric Source	Rubric Type	HealthBench	ArgQuality	HelpSteer	Execution (s)↓
No Rubrics	Black-Box Agentic Evaluation (GPT 5.5 All Queries)	.639	.904	.790	.7393
Human	Natural Language Rubrics (Qwen 30B Per Query)	.522	.904	.623	1.688
GPT-5.5	Executable Rubrics	.529	.809	.640	.0109
	Executable Rubrics + Popular Tools	.525	.798	.737	.6518
	Executable Rubrics + Deterministic Tools	.486	.819	.660	.4187
Gemini 3.5 Flash	Executable Rubrics	.482	.819	.753	.0088
	Executable Rubrics + Popular Tools	.427	.702	.583	.5707
	Executable Rubrics + Deterministic Tools	.518	.872	.587	.1189
Claude Sonnet 4.6	Executable Rubrics	.400	.755	.647	.0229
	Executable Rubrics + Popular Tools	.514	.670	.633	.9062
	Executable Rubrics + Deterministic Tools	.416	.915	.700	.1293

Table 1: Performance comparison across rubric sources and benchmarks. The first column depicts the source of the rubrics created once per corpus. Except for the first row, all evaluations have been done querywise. The first two rows require LLMs for evaluation, while the bottom nine rows generate scores using executable rubrics. Last column is averaged across three datasets.

medical red-flag detection, refusal-policy matching, markdown-table detection, readability scoring, keyword coverage, language matching, and actionable-harm detection. This setup lets the model write rubric programs that call concrete tools allowing arbitrary custom logic to enrich the evaluation.

5 Results and Analysis

We report preference accuracies in Table 1. **Overall, executable rubrics recover substantial preference signal without invoking an LLM judge at evaluation time. The strongest executable variant exceeds the natural-language rubric baseline on all three benchmarks, though the size and source of the gain vary substantially across datasets.** Natural-language rubrics are not consistently effective when evaluated with Qwen3-30B-Instruct-A3B. They match the direct GPT-5.5 baseline on ArgQuality (.904), but perform substantially worse on HealthBench (.522 vs. .639) and HelpSteer (.623 vs. .790). This suggests that natural-language rubrics remain dependent on the judge model used to interpret each criterion. Executable rubrics improve over the natural-language rubric baseline on all three benchmarks. The best executable systems reach .529 on HealthBench, .915 on ArgQuality, and .753 on HelpSteer, compared with .522, .904, and .623 for natural-language rubrics. These results suggest that deterministic scoring programs can recover much of the preference signal captured by NL rubric judging, while replacing repeated black-box criterion interpretation with explicit executable logic. Deterministic tools are especially helpful on ArgQuality, improving performance for all three rubric generators and yielding the best overall score of .915

with Claude Sonnet 4.6. On HelpSteer, deterministic tools modestly improve GPT-5.5 and Claude-generated rubrics from .640 to .660 and from .647 to .700, respectively, although the best executable result of .753 is obtained by Gemini 3.5 Flash without tool augmentation. However, on HealthBench, tool use is less reliable and does not close the gap with direct GPT-5.5 evaluation. In summary, executable rubrics provide a transparent and judge-free alternative to natural-language rubric evaluation. They are strongest when evaluation criteria can be expressed through explicit textual checks, but their performance still depends on the benchmark, the rubric generator, and the available tool interface. **Besides, executable rubrics are considerably faster** as shown in the execution times in Appendix Table 3 as compared to their NL counterparts. For instance, standard executable rubrics generated by Gemini 3.5 Flash achieved an overall average speedup of $\sim 192\times$ compared to the Qwen-30B NL judge (0.0088s vs. 1.688s). Also note that efficiency-focused models (like Gemini 3.5 Flash) sometimes produce “no-op” or shallow tool wrappers rather than deeply integrating heavy NLP pipelines due to misunderstanding the task. This failure mode leads to artificially low latency (up to $327\times$ faster than the NL baseline on HealthBench) but severely degrades preference accuracy (.427). Executable rubrics from GPT 5.5 and Claude are shown in the Appendix Figures 2 and 3.

6 Conclusion and Future Work

We introduced *ExecRubrics*, a framework for turning natural-language rubrics into executable scoring programs. Unlike conventional rubric evaluators, which require an LLM or human judge to

interpret each criterion, executable rubrics make evaluation logic explicit: they can encode complex logic as deterministic code.

Across HealthBench, ArgQuality, and HelpSteer, generated executable rubrics recover substantial preference signals without requiring a black-box LLM at evaluation time. The strongest executable variants outperform the natural-language rubric baseline on all three benchmarks. Moreover, tool-augmented rubrics demonstrate that deterministic tools, such as NLP libraries, can provide useful and transparent primitives for evaluation. These results suggest that executable rubrics are a promising intermediate representation for auditable, modifiable, and efficient LLM evaluation.

Our experiments study executable rubrics as automatically generated evaluators, and they point to several interesting directions for future work. First, we instruct models to generate rubrics that operate over the full response text. This makes the setup simple, broadly applicable, and easy to execute across domains, but different domains may require different levels of granularity. In high-stakes settings such as medicine, high-precision checks over specific symptoms, entities, contraindications, or safety actions can be especially important, because small omissions or unsafe recommendations may materially change the quality of an answer. In more open-ended settings, however, very precise lexical or structural checks may be less desirable, since there may be many valid ways to satisfy the same evaluation intent. Future work could therefore adapt the granularity of executable rubrics to the domain by incorporating explicit parsing, sentence-level decomposition, claim extraction, domain-specific entity recognition, or typed intermediate representations before scoring.

Future work should also study how humans inspect, revise, and debug executable rubrics; how rubric programs can be made more robust across domains; and how executable evaluation logic can support dataset filtering, reward modeling, preference optimization while avoiding hacking. More broadly, *ExecRubrics* points toward evaluation systems whose judgments are accurate, explainable and operationally inspectable.

7 Limitations

Second, although executable rubrics are intended to be more interpretable because their scoring logic is explicit, we do not directly evaluate human in-

terpretability which could often be subjective. In practice, there is likely a balance between expressivity and interpretability. More expressive rubric programs can capture dependencies, alternatives, penalties, and override conditions, but they may also become more complex for humans to inspect and revise. Conversely, flatter and more generic rubrics may be easier to read, but they can fail to express the evaluation structure needed for accurate preference judgments, as suggested by the comparatively lower performance of natural-language rubrics in our preference analysis. Future work could therefore study how humans write, inspect, debug, and simplify executable rubrics, and how interfaces can expose the underlying logic without making the representation tedious to use.

Third, executable rubrics may be vulnerable to gaming. Since their scoring logic is explicit, response generators could learn to trigger specific textual, structural, or semantic checks without satisfying the underlying evaluation intent. This risk is especially important if executable rubrics are used as reward signals for RL optimization. Future work should study adversarial robustness and whether executable rubric scores remain aligned with human judgments under optimization pressure.

As frontier models become increasingly capable of scraping and extracting publicly visible data with high accuracy, the risk of memorization cannot be ignored. The performance of executable rubrics, especially on datasets such as HelpSteer and ArgQuality, may be influenced in part by memorized content. However, we also believe that predicting dictionaries, loops, and generic logic should not necessarily be attributed directly to memorization, since such patterns commonly appear throughout LLMs’ pretraining and midtraining data.

8 Ethical Considerations

LLMs are increasingly used as evaluators, but LLM judges are black boxes whose scoring behavior can be difficult to inspect, reproduce, or contest. This opacity raises concerns about accountability, bias, and overreliance on automated judgments, especially in high-stakes settings. Our work aims to make rubric-based evaluation more responsible by replacing repeated black-box criterion interpretation with explicit executable scoring logic. Because executable rubrics expose the rules, branches, penalties, and tool calls used during evaluation, they can be inspected, audited, revised, and stress-

tested more directly than opaque judge-model outputs. However, executable rubrics are not inherently fair or correct: poorly written rules may encode bias, miss valid response variations, or overfit to superficial textual cues. We therefore view *ExecRubrics* as a step toward more transparent and accountable evaluation, not as a substitute for human oversight, domain expertise, or careful validation.

The experiments in this paper were mostly conducted using GPT 5.5 Codex² and Gemini CLIs.³ Some paragraphs of the paper were grammatically corrected using ChatGPT 5.5 (OpenAI, 2026).

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References

- Afra Feyza Akyürek, Advait Gosai, Chen Bo Calvin Zhang, Vipul Gupta, Jaehwan Jeong, Anisha Gunjal, Tahseen Rabbani, Maria Mazzone, David Randolph, Mohammad Mahmoudi Meymand, et al. 2025. Prbench: Large-scale expert rubrics for evaluating high-stakes professional reasoning. *arXiv preprint arXiv:2511.11562*.
- Anthropic. 2026. Introducing Claude Sonnet 4.6. <https://www.anthropic.com/news/claude-sonnet-4-6>.
- Burouj Armgaan, Manthan Dalmia, Sourav Medya, and Sayan Ranu. 2024. Graphtrail: Translating gnn predictions into human-interpretable logical rules. *Advances in Neural Information Processing Systems*, 37:123443–123470.
- Rahul K Arora, Jason Wei, Rebecca Soskin Hicks, Preston Bowman, Joaquin Quiñero-Candela, Foivos Tsimpourlas, Michael Sharman, Meghan Shah, Andrea Vallone, Alex Beutel, et al. 2025. Healthbench: Evaluating large language models towards improved human health. *arXiv preprint arXiv:2505.08775*.
- Onur Asan, Alparslan Emrah Bayrak, and Avishek Choudhury. 2020. Artificial intelligence and human trust in healthcare: focus on clinicians. *Journal of medical Internet research*, 22(6):e15154.
- Steven Bird. 2006. Nltk: the natural language toolkit. In *Proceedings of the COLING/ACL 2006 interactive presentation sessions*, pages 69–72.
- Param Biyani, Yasharth Bajpai, Arjun Radhakrishna, Gustavo Soares, and Sumit Gulwani. 2024. Rubicon: Rubric-based evaluation of domain-specific human ai conversations. In *Proceedings of the 1st ACM International Conference on AI-Powered Software*, pages 161–169.
- Haolin Chen, Deon Metelski, Leon Qi, Tao Xia, Joonyul Lee, Steve Brown, Kevin Riley, Frank Wang, TY Liu, Hank Capps MD, et al. 2026. Chi-bench: Can ai agents automate end-to-end, long-horizon, policy-rich healthcare workflows? *arXiv preprint arXiv:2605.16679*.
- Philip Chung, Akshay Swaminathan, Alex J. Goodell, Yeasul Kim, S. Momeni Reincke, Lichy Han, Ben Deverett, Mohammad Amin Sadeghi, Abdel-Badih Ariss, Marc Ghanem, David Seong, Andrew A. Lee, Caitlin E. Coombes, Brad Bradshaw, Mahir A. Sufian, Hyo Jung Hong, Teresa P. Nguyen, Mohammad R. Rasouli, Komal Kamra, Mark A. Burbridge, James C. McAvoy, Roya Saffary, Stephen P. Ma, Dev Dash, James Xie, Ellen Y. Wang, Clifford A. Schmiesing, Nigam Shah, and Nima Aghaeipour. 2026. Verifying facts in patient care documents generated by large language models using electronic health records. *NEJM AI*, 3(1):AIdbp2500418.
- Aubrey Condor, Zachary Pardos, and Marcia Linn. 2022. Representing scoring rubrics as graphs for automatic short answer grading. In *International Conference on Artificial Intelligence in Education*, pages 354–365. Springer.
- Jonathan Cook, Tim Rocktäschel, Jakob Foerster, Dennis Aumiller, and Alex Wang. 2024. Ticking all the boxes: Generated checklists improve llm evaluation and generation. *arXiv preprint arXiv:2410.03608*.
- Miles Cranmer, Alvaro Sanchez Gonzalez, Peter Battaglia, Rui Xu, Kyle Cranmer, David Spergel, and Shirley Ho. 2020. Discovering symbolic models from deep learning with inductive biases. *Advances in neural information processing systems*, 33:17429–17442.
- Kaustubh Dhole and Eugene Agichtein. 2024. Llm judges for retrieval augmented argumentation.
- Kaustubh Dhole, Ramraj Chandradevan, and Eugene Agichtein. 2025a. Adverser: Adversarial robustness testing and training of llm-based groundedness evaluators via semantic structure manipulation. In *Proceedings of the 14th Joint Conference on Lexical and Computational Semantics (*SEM 2025)*, pages 395–408.
- Kaustubh Dhole, Kai Shu, and Eugene Agichtein. 2025b. Conqret: A new benchmark for fine-grained automatic evaluation of retrieval augmented computational argumentation. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5687–5713.
- Kaustubh D. Dhole and Eugene Agichtein. 2026. Rubricrag: Towards interpretable and reliable llm evaluation via domain knowledge retrieval for rubric generation. In *Proceedings of the ACM SIGIR Conference*

²<https://chatgpt.com/codex/>

³<https://gemini-cli.com/>

- on Research and Development in Information Retrieval. Accepted at SIGIR 2026.
- Naghmeh Farzi and Laura Dietz. 2025. Criteria-based llm relevance judgments. In *Proceedings of the 2025 International ACM SIGIR Conference on Innovative Concepts and Theories in Information Retrieval (IC-TIR)*, pages 254–263.
- Chase M Fensore, Kaustubh Dhole, Jason Fan, Eugene Agichtein, and Joyce C Ho. 2026. How fine-grained should a rag benchmark be? a hierarchical framework for synthetic question generation. *arXiv preprint arXiv:2606.12789*.
- Lukas Gienapp, Benno Stein, Matthias Hagen, and Martin Potthast. 2020. Efficient pairwise annotation of argument quality. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5772–5781.
- Google. 2026. Gemini 3.5: Frontier Intelligence with Action. <https://deepmind.google/blog/gemini-3-5-frontier-intelligence-with-action/>.
- Paul Hager, Friederike Jungmann, Robbie Holland, Kunal Bhagat, Inga Hubrecht, Manuel Knauer, Jakob Vielhauer, Marcus Makowski, Rickmer Braren, Georgios Kaissis, et al. 2024. Evaluation and mitigation of the limitations of large language models in clinical decision-making. *Nature medicine*, 30(9):2613–2622.
- Rebecca Soskin Hicks, Mikhail Trofimov, Dominick Lim, Rahul K Arora, Foivos Tsimpourlas, Preston Bowman, Michael Sharman, Chi Tong, Kavin Karthik, Arnav Dugar, et al. 2026. Healthbench professional: Evaluating large language models on real clinician chats. Technical report, tech. rep., OpenAI.
- Matthew Honnibal, Ines Montani, Sofie Van Landeghem, and Adriane Boyd. 2020. *spacy: Industrial-strength natural language processing in python*.
- Yeonseok Jeong, Minsoo Kim, Seung-won Hwang, and Byung-Hak Kim. 2025. *Agent-as-judge for factual summarization of long narratives*. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing*, pages 23591–23608, Suzhou, China. Association for Computational Linguistics.
- Sayash Kapoor, Peter Kirgis, Andrew Schwartz, Stephan Rabanser, JJ Allaire, Rishi Bommasani, Harry Coppock, Magda Dubois, Gillian K Hadfield, Andrew B Hall, et al. 2026. Open-world evaluations for measuring frontier ai capabilities. *arXiv preprint arXiv:2605.20520*.
- Bryan Li, William Walden, Yu Hou, Gabrielle Kaili-May Liu, Dawn Lawrie, Jame Mayfield, Eugene Yang, Chris Callison-Burch, and Laura Dietz. 2026. Dogmatiq: Automated generation of question-and-answer nuggets for report evaluation. *arXiv preprint arXiv:2605.04458*.
- Jinrong Li and Peggy Lindsey. 2015. Understanding variations between student and teacher application of rubrics. *Assessing writing*, 26:67–79.
- Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. 2023. *G-eval: NLG evaluation using gpt-4 with better human alignment*. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 2511–2522, Singapore. Association for Computational Linguistics.
- Neil Mallinar, A Ali Heydari, Xin Liu, Anthony Z Faranesh, Brent Winslow, Nova Hammerquist, Benjamin Graef, Cathy Speed, Mark Malhotra, Shwetak Patel, et al. 2026. A scalable framework for evaluating health language models. *npj Digital Medicine*.
- Sewon Min, Kalpesh Krishna, Xinxu Lyu, Mike Lewis, Wen-tau Yih, Pang Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2023. Factscore: Fine-grained atomic evaluation of factual precision in long form text generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 12076–12100.
- Tong Mu, Alec Helyar, Johannes Heidecke, Joshua Achiam, Andrea Vallone, Ian Kivlichan, Molly Lin, Alex Beutel, John Schulman, and Lilian Weng. 2024. Rule based rewards for language model safety. *Advances in Neural Information Processing Systems*, 37:108877–108901.
- OpenAI. 2026. Introducing GPT-5.5. <https://openai.com/index/introducing-gpt-5-5/>.
- Long Phan, Alice Gatti, Ziwen Han, Nathaniel Li, Josephina Hu, Hugh Zhang, Chen Bo Calvin Zhang, Mohamed Shaaban, John Ling, Sean Shi, et al. 2025. Humanity’s last exam. *arXiv preprint arXiv:2501.14249*.
- W James Popham. 1997. What’s wrong-and what’s right-with rubrics. *Educational leadership*, 55:72–75.
- Daking Rai, Mor Geva, and Ziyu Yao. 2026. Data-driven circuit discovery for interpretability of language models. *arXiv preprint arXiv:2605.09129*.
- Marco Tulio Ribeiro, Tongshuang Wu, Carlos Guestrin, and Sameer Singh. 2020. *Beyond accuracy: Behavioral testing of NLP models with CheckList*. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4902–4912, Online. Association for Computational Linguistics.
- Joel Rorseth, Parke Godfrey, Lukasz Golab, Divesh Srivastava, and Jarek Szlichta. 2026. Ruben: Rule-based explanations for retrieval-augmented llm systems. *arXiv preprint arXiv:2605.10862*.
- Shangeetha Sivasothy, Adrian Bingham, Irini Logothetis, Scott Barnett, Mohamed Abdelrazek, Carl Luckhoff, Joseph Mathew, Rajesh Vasa, and Kon

- Mouzakis. 2026. Large language models and conditional rules in clinical decision support systems. *Health Information Science and Systems*, 14(1):32.
- Yiyou Sun, Xinyang Han, Weichen Zhang, Yuanbo Pang, Tianyu Wang, Yuhao Cao, Yixiao Huang, Chris Duroiu, Haoyun Zhang, Jeffrey Lin, Weishu Zhang, Tyler Zeng, Ying Yan, Bo Liu, Hanson Wen, Mingyang Xu, Xiaoyuan Liu, Zimeng Chen, Weiyan Shi, Amanda Dsouza, Vincent Sunn Chen, Patrick Bryant, Carl Boettiger, Yamini Rangan, Bradley Rothenberg, Kyle Steinfeld, Arvind Rao, Tapio Schneider, Georgios Yannakakis, Laure Zanna, Kaan Ozbay, Ida Sim, Tarek Zohdi, George Em Karniadakis, Jack Gallant, Teresa Head-Gordon, Yushan Li, Wenxi Deng, Tao Sun, Huiqi Wang, Zhun Wang, Justin Xu, Chris Yuhao Liu, Yafei Cheng, Rongwang Hu, Aras Bacho, Shengcao Cao, Zengyi Qin, Yixiong Chen, Hengduan Fan, Hao Liu, Lin Zeng, Shashank Muralidhar Bharadwaj, Litian Gong, Yingxuan Yang, Maojia Song, Ruheng Wang, Zongzheng Zhang, Honglin Bao, Shuo Lu, Jianhong Tu, Zhonghua Wang, Zheng Zhang, Zijiao Chen, Yanqiong Jiang, Zhendong Li, Bohan Lyu, Chang Ma, Peiran Xu, Benran Zhang, Shangding Gu, Haoyue Hua, Haoyang Li, Wanthe Liao, Chengzhi Liu, Junbo Peng, Haoran Sun, Zechen Xu, Bo Chen, Jiayi Cheng, Yi Jiang, Keying Kuang, Yuan Li, Youbang Pan, Ziyao Rao, Alexander Schubert, Yifan Shen, Vincent Siu, Xiatao Sun, Kangqi Zhang, Xiaopan Zhang, Yuchen Zhu, Ishaan Singh Chandok, Lei Ding, Jingxuan Fan, Andrew Glover, Jiaming Hu, Yiran Hu, Wenbo Huang, Zixin Jiang, Haoran Jin, Lukas Kim, Ming Liu, Yang Liu, Alireza Rafiei, Xuhuan Shen, Kunyang Sun, Sophia Sun, Ting Sun, Eric Wang, Yixin Wang, Hanwen Xing, Sihan Xu, Yuzheng Xu, Zhongxing Xu, Zhiling Yan, Boqin Yuan, Ruiqi Zhang, Yifan Zhang, Zibo Zhao, Liana, Santanu Bosu Antu, Haoyue Bai, Carlo Bosio, Joseph Cavanagh, Patricia Cavazos-Rehg, Tianxing Chen, Xuewen Chen, Yipu Chen, Chenyu Zhu, Chen Dai, Stefano De Castro, Yunfu Deng, Kaustubh Dhole, Jiayuan Ding, Chenchen Du, Zhehang Du, Hao Fan, Run-Ze Fan, Hengyu Fu, Shi Gu, Yifan Gu, Charlie Guo, Baihe Huang, Baixiang Huang, Rimika Jaiswal, Zhihan Jiang, Ran Jin, Erin Kasson, Xin Lan, Joseph Lee, Deren Lei, Chenyu Li, Daofeng Li, Haitao Li, Hongwei Li, Jingyan Li, Xiao Li, Yi Li, Yinsheng Li, Yuangang Li, Zhixu Li, Wenyu Liang, Longtai Liao, Kevin Qinghong Lin, Andy Zeyi Liu, Che Liu, Jiaming Liu, Kaiyuan Liu, Xuan Liu, Pan Lu, Wenbo Lv, Yicheng Lyu, Qiuyang Mang, Kyle Montgomery, Yuzhou Nie, Ruoxi Ning, Jorin Overwiening, Xu Pan, Layna Paraboschi, Core Francisco Park, Justin Purnomo, Swati Rajwal, Scott Rankin, Bixuan Ren, Yiren Rong, HaoYang Shang, Ventus Shaw, Fiona Shen, Jiawei Shen, Minqi Shi, Shi Qiu, Huaxiu Yao, Tianneng Shi, Jonah So, Vladislav Susoy, Hannah Szlyk, Haocheng Wang, Jialu Wang, Wei Wang, Xinyu Wang, Zehao Wang, Dowling Wong, Angela Wu, Dehao Wu, Fangyu Wu, Mengyuan "Millie" Wu, Yu Wu, Yuchen Wu, Yuhao Wu, Qingpo Wuwu, Weihang Xiao, Yongyi Xiong, Fan Xu, Ruiling Xu, Mingxuan Yan, Benjamin Yang, Jirong Yang, Sen Yang, Xiaoli Yang, Yushi Yang, Haoran Ye, Xiaohu Yu, Zhengming Yu, Chenlong Zhang, Chi Zhang, Hanning Zhang, Hanwen Zhang, Junge Zhang, Kunpeng Zhang, Song Zhang, Wenjin Zhang, Wenshuo Zhang, Ying Zhang, Yizhi Zhang, Brian Zhao, Qijian Zhao, Yimin Zhao, Yuhaozhua Zheng, Liwei Zhou, Tianyue Zhou, Sichen Zhu, Siqi Zhu, Yan Zhu, Yishu Zhu, Jierui Zuo, Chonghao Cai, Helena Casademunt, Wenjia Chen, Cheng Cheng, Nawen Deng, Rao Fu, Tianfu Fu, Yifan Han, He Ren, Zhenyu He, Qiao Jin, Langlang Li, Yuetai Li, Sylvia Liu, Lu Lu, Luqing Zhou, Subhabrata Mukherjee, Yunqi Ouyang, Yin Ren, Dawei Shi, Haoran Wu, Zhiyue Wu, Hannah Yao, Zhuoran Yi, Jenny Yu, Rhea Zhan, Hang Zhou, Blake Zhu, Junfan Zhu, Alan Yuille, Yang Liu, Russell Alan Poldrack, Jiachen Li, Zhenglu Li, Molei Tao, Jing Huang, Wenqi Shi, Costas Spanos, Lichao Sun, Chenguang Wang, Orson Xu, Zhen Dong, Hector Gomez, Aylin Caliskan, Ali Emami, Haimin Hu, Zhi Li, Lihui Liu, Murphy Niu, Yi Shao, Jianxin Sun, Mikko Tolonen, Ting Wang, Sanjiv Das, Yanjun Gao, Wenbo Guo, Erika J Schneider, Zhiyong Lu, Yian Ma, Mark Mueller, Radha Poovendran, Somayeh Sojoudi, Yinglun Zhu, and Dawn Song. 2026. [Agents' last exam](#).
- Yufei Wang, Can Xu, Huang Hu, Chongyang Tao, Stephen Wan, Mark Dras, Mark Johnson, and Daxin Jiang. 2021. Neural rule-execution tracking machine for transformer-based text generation. *Advances in Neural Information Processing Systems*, 34:16938–16950.
- Zhilin Wang, Yi Dong, Jiaqi Zeng, Virginia Adams, Makesh Narsimhan Sreedhar, Daniel Egert, Olivier Delalleau, Jane Scowcroft, Neel Kant, Aidan Swope, et al. 2024. Helpsteer: Multi-attribute helpfulness dataset for steerlm. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 3371–3384.
- Zhilin Wang, Jaehun Jung, Ximing Lu, Shizhe Diao, Ellie Evans, Jiaqi Zeng, Pavlo Molchanov, Yejin Choi, Jan Kautz, and Yi Dong. 2025. Profbench: Multi-domain rubrics requiring professional knowledge to answer and judge. *arXiv preprint arXiv:2510.18941*.
- An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, et al. 2025. Qwen3 technical report. *arXiv preprint arXiv:2505.09388*.
- Seonghyeon Ye, Doyoung Kim, Sungdong Kim, Hyeonbin Hwang, Seungone Kim, Yongrae Jo, James Thorne, Juho Kim, and Minjoon Seo. 2024. [FLASK: Fine-grained language model evaluation based on alignment skill sets](#). In *The Twelfth International Conference on Learning Representations*.

A Rubric Types

Benchmark	Rubric Criteria	# Test
HealthBench	Communication Quality, Accuracy, Completeness, Context Awareness, Instruction Following	255
HelpSteer	Helpfulness, Correctness, Coherence, Complexity, Verbosity	300
ArgQuality	Cogency, Local Acceptability, Local Relevance, Local Sufficiency, Effectiveness, Credibility, Emotional Appeal, Clarity, Appropriateness, Arrangement, Reasonableness, Global Acceptability, Global Relevance, Global Sufficiency	94

Table 2: Rubric criteria and number of test examples used for each benchmark.

NL Rubrics (as measured on NVIDIA H200)		Executable Rubrics			
NL Rubric Approach	Time (s)	Executable Approach	GPT-5.5	Gemini 3.5 Flash	Sonnet 4.6
Qwen3-14B	2.0173	Human to Executable	.0106	.0098	.0085
Qwen3-30B-A3B-Instruct-2507	1.7316	+ Popular Tools	.3932	.0053	.5405
Llama-3.1-8B-Instruct	1.4058	+ DetTools	.8402	.0975	.0575

Table 3: Average per-query preference evaluation time in seconds on HealthBench. Executable-rubric evaluation is considerably faster, relative to NL Rubrics even on NVIDIA H200.

Executable Rubric Generated by GPT 5.5 for ArgQuality

Figure 2: GPT 5.5 generated executable rubric for evaluating the 14 dimensions of ArgQuality long-form arguments. Functions of the 3 of the dimensions (cogency, local acceptability, and global sufficiency) have been shown. The final `score_response` function calls each of the 14 functions and returns the sum of them as the evaluation score. The source prompt has been shown in Figure 4.

Executable rubrics for 3 dimensions “cogency”, “local acceptability” and “global sufficiency”

```
import re
_WORD_RE = re.compile(r"[a-zA-Z][a-zA-Z']-*")
_SENTENCE_RE = re.compile(r"^[.!?]+[.!?]?")

DISCOURSE_MARKERS = {
    "because", "since", "therefore", "thus", "hence",
    "so", "consequently",
    "as a result", "for this reason", "this means",
    "shows that", "suggests that",
    "indicates that", "implies that", "leads to"
}

CONCLUSION_MARKERS = {
    "therefore", "thus", "hence", "so", "consequently",
    "in conclusion",
    "overall", "for these reasons", "we should", "we must",
    "it follows",
    "this shows", "this suggests", "i conclude", "the conclusion"
}

PREMISE_MARKERS = {
    "because", "since", "given that", "as", "for example",
    "for instance",
    "evidence", "reason", "one reason", "another reason",
    "data", "study",
    "research", "statistics", "according to",
    "reported", "survey", "case"
}

COUNTERARGUMENT_MARKERS = {
    "however", "although", "though", "while", "on the other hand",
    "critics",
    "opponents", "some argue", "one objection",
    "counterargument", "nevertheless",
    "but", "despite", "admittedly", "to be fair", "even if",
    "tradeoff", "trade-off"
}

EVIDENCE_MARKERS = {
    "for example", "for instance", "evidence", "data",
    "study", "studies",
    "research", "survey", "statistics", "percent", "%",
    "according to",
    "reported", "analysis", "case", "expert", "source",
    "historically"
}
```

```
CAUTION_MARKERS = {
    "may", "might", "can", "could", "often", "usually",
    "in many cases",
    "likely", "appears", "suggests", "depending",
    "some", "many", "generally",
    "not always", "tends to", "plausibly"
}

ABSOLUTE_MARKERS = {
    "always", "never", "everyone", "nobody", "all",
    "none", "completely",
    "totally", "undeniably", "obviously", "clearly",
    "proves", "without exception",
    "guaranteed", "must be true"
}

INSULT_MARKERS = {
    "idiot", "stupid", "moron", "dumb", "evil", "trash",
    "liar", "crazy",
    "pathetic", "worthless", "corrupt", "brainwashed",
    "fool", "shut up"
}

PROFANITY_MARKERS = {
    "damn", "hell", "shit", "crap", "fuck", "fucking",
    "bullshit"
}

EMOTIONAL_MARKERS = {
    "harm", "danger", "fear", "hope", "fair", "unfair",
    "justice", "suffering",
    "protect", "threat", "risk", "compassion",
    "dignity", "rights", "urgent",
    "families", "children", "community", "future",
    "crisis"
}

MANIPULATIVE_MARKERS = {
    "any decent person", "only a monster", "you must be heartless",
    "if you disagree", "real people know", "wake up",
    "be afraid",
    "they are coming for", "destroy our lives", "no sane person"
}

VAGUE_MARKERS = {
    "things", "stuff", "bad", "good", "many people say",
    "somehow",
    "obviously", "basically", "a lot", "huge", "big problem",
    "nice",
    "very important"
}

STRUCTURE_MARKERS = {
    "first", "second", "third", "finally", "in conclusion",
    "overall",
    "one reason", "another reason", "moreover",
    "furthermore", "also",
    "however", "therefore"
}

QUESTION_STOPWORDS = {
    "the", "a", "an", "and", "or", "but", "if", "then",
    "to", "of", "in", "on",
    "for", "with", "by", "from", "as", "is", "are",
    "was", "were", "be", "been",
    "being", "do", "does", "did", "should", "would",
    "could", "can", "may",
    "might", "must", "will", "shall", "it", "this",
    "that", "these", "those",
}
```

```

    "i", "you", "we", "they", "he", "she", "them",
    "his", "her", "their",
    "our", "your", "about", "into", "than", "too",
    "very", "not", "no", "yes",
    "there", "here", "such", "which", "what", "who",
    "whom", "when", "where",
    "why", "how", "whether", "issue", "claim", "stance",
    "argument", "argue"
}

def score_cogency(query: str, text: str):
    max_possible = 10
    reasons = []
    q = (query or "").lower()
    t = (text or "").lower()
    words = _WORD_RE.findall(t)
    sentences = [s.strip() for s in
        _SENTENCE_RE.findall(text or "") if s.strip()]
    score = 0

    has_conclusion = any(m in t for m in
        CONCLUSION_MARKERS) or
        bool(re.search(r"\b(should|must|ought to|need to|is
            better|is worse)\b", t))
    premise_count = sum(1 for m in PREMISE_MARKERS if m
        in t)
    relation_count = sum(1 for m in DISCOURSE_MARKERS if
        m in t)
    has_counter = any(m in t for m in
        COUNTERARGUMENT_MARKERS)
    has_evidence = any(m in t for m in EVIDENCE_MARKERS)
    circular =
        bool(re.search(r"\bbecause\b[^\!?\]{0,80}\bbecause\b",
            t)) and len(set(words)) < max(20, len(words) * 0.35)
    off_topic_tokens = set(w for w in
        _WORD_RE.findall(q) if len(w) > 3 and w not in
        QUESTION_STOPWORDS)
    text_tokens = set(w for w in words if len(w) > 3)
    overlap_ratio = len(off_topic_tokens & text_tokens)
        / len(off_topic_tokens) if off_topic_tokens else 0.5

    if len(words) >= 40:
        score += 1.0
        reasons.append("Argument has enough length to
            develop a line of reasoning.")
    else:
        reasons.append("Argument is too short to
            establish strong cogency.")

    if has_conclusion:
        score += 2.0
        reasons.append("Identifiable conclusion or
            stance is present.")
    else:
        score -= 2.0
        reasons.append("No clear conclusion or stance is
            identifiable.")

    if premise_count >= 2:
        score += 2.0
        reasons.append("Multiple premise or support
            markers are present.")
    elif premise_count == 1:
        score += 1.0
        reasons.append("At least one premise marker is
            present.")
    else:
        score -= 1.5
        reasons.append("Premises are not clearly
            signaled.")

    if relation_count >= 2:
        score += 2.0
        reasons.append("Logical links between premises
            and conclusion are explicit.")
    elif relation_count == 1:
        score += 1.0
        reasons.append("Some logical relation is
            signaled.")
    else:
        reasons.append("Logical relation between support
            and conclusion is weakly signaled.")

    if has_evidence:
        score += 1.0

```

```

        reasons.append("Argument includes evidence-like
            support.")
    else:
        reasons.append("Argument lacks evidence-like
            support.")

    if has_counter:
        score += 1.0
        reasons.append("Argument acknowledges contrast,
            tradeoff, or objection.")
    else:
        reasons.append("No counterargument or limitation
            is considered.")

    if overlap_ratio >= 0.35:
        score += 1.0
        reasons.append("Argument appears connected to
            the issue in the query.")
    else:
        score -= 2.0
        reasons.append("Argument appears weakly
            connected to the issue in the query.")

    if circular:
        score -= 2.0
        reasons.append("Argument may rely on repetitive
            or circular reasoning.")

    score = max(0, min(score, max_possible))
    return {"score": score, "max_possible":
        max_possible, "reasons": reasons}

def score_global_sufficiency(query: str, text: str):
    max_possible = 10
    reasons = []
    t = (text or "").lower()
    words = _WORD_RE.findall(t)
    score = 0

    counter_count = sum(1 for m in
        COUNTERARGUMENT_MARKERS if m in t)
    rebuttal_markers = {
        "however", "nevertheless", "still", "even so",
        "despite", "but",
        "this objection", "this concern", "can be
            addressed", "respond", "rebut",
        "tradeoff", "trade-off", "on balance"
    }
    rebuttal_count = sum(1 for m in rebuttal_markers if
        m in t)
    evidence_count = sum(1 for m in EVIDENCE_MARKERS if
        m in t)
    conclusion_found = any(m in t for m in
        CONCLUSION_MARKERS) or
        bool(re.search(r"\b(should|must|ought to|need
            to)\b", t))
    caution_found = any(re.search(r"\b" + re.escape(m) +
        r"\b", t) for m in CAUTION_MARKERS)

    if counter_count >= 2:
        score += 3.0
        reasons.append("Argument anticipates multiple
            objections or tradeoffs.")
    elif counter_count == 1:
        score += 2.0
        reasons.append("Argument anticipates at least
            one objection or tradeoff.")
    else:
        score -= 1.5
        reasons.append("Argument does not anticipate
            counterarguments.")

    if rebuttal_count >= 2:
        score += 2.0
        reasons.append("Argument contains explicit
            rebuttal or balancing language.")
    elif rebuttal_count == 1:
        score += 1.0
        reasons.append("Argument contains some rebuttal
            or balancing language.")

    if evidence_count >= 1:
        score += 1.5
        reasons.append("Rebuttal or overall argument has
            evidence-like support.")
    else:

```

```

        reasons.append("Counterargument handling lacks
        evidence-like support.")

    if conclusion_found:
        score += 1.5
        reasons.append("Argument reaches an overall
        conclusion after support.")
    else:
        score -= 1.0
        reasons.append("Argument lacks an overall
        conclusion.")

    if caution_found:
        score += 1.0
        reasons.append("Qualified language helps handle
        exceptions.")
    else:
        reasons.append("Argument could better handle
        exceptions with qualification.")

    if len(words) >= 70:
        score += 1.0
        reasons.append("Argument has enough development
        for global sufficiency.")
    elif len(words) < 35:
        score -= 1.0
        reasons.append("Argument is too short for global
        sufficiency.")

    if sum(1 for m in ABSOLUTE_MARKERS if
    re.search(r"\b" + re.escape(m) + r"\b", t)) > 2:
        score -= 1.0
        reasons.append("Too many absolute claims weaken
        sufficiency against objections.")

    score = max(0, min(score, max_possible))
    return {"score": score, "max_possible":
    max_possible, "reasons": reasons}

def score_local_acceptability(query: str, text: str):
    max_possible = 10
    reasons = []
    t = (text or "").lower()
    words = _WORD_RE.findall(t)
    score = 0

    evidence_count = sum(1 for m in EVIDENCE_MARKERS if
    m in t)
    caution_count = sum(1 for m in CAUTION_MARKERS if
    re.search(r"\b" + re.escape(m) + r"\b", t))
    absolute_count = sum(1 for m in ABSOLUTE_MARKERS if
    re.search(r"\b" + re.escape(m) + r"\b", t))
    insult_count = sum(1 for m in INSULT_MARKERS if
    re.search(r"\b" + re.escape(m) + r"\b", t))
    vague_count = sum(1 for m in VAGUE_MARKERS if m in
    t)
    numbers = len(re.findall(r"\b\d+(?:\.\d+)?%\b", t))

    if evidence_count >= 2:
        score += 3.0
        reasons.append("Premises include several
        evidence-like supports.")
    elif evidence_count == 1:
        score += 1.5
        reasons.append("Premises include at least one
        evidence-like support.")
    else:
        reasons.append("Premises are mostly unsupported
        by evidence markers.")

    if caution_count >= 2:
        score += 2.0
        reasons.append("Claims use appropriately
        cautious wording.")
    elif caution_count == 1:
        score += 1.0
        reasons.append("Some cautious wording is
        present.")

    if numbers > 0:
        score += 1.0
        reasons.append("Argument includes quantitative
        or concrete detail.")

    if len(words) >= 50 and len(set(words)) / max(1,
    len(words)) >= 0.35:

```

```

        score += 2.0
        reasons.append("Premises are developed with
        non-trivial lexical variety.")
    elif len(words) >= 30:
        score += 1.0
        reasons.append("Premises have some
        development.")

    if absolute_count == 0:
        score += 1.0
        reasons.append("Argument avoids unsupported
        absolute claims.")
    else:
        score -= min(2.5, absolute_count * 0.8)
        reasons.append("Argument uses broad absolute
        claims that may be unacceptable.")

    if insult_count == 0:
        score += 1.0
        reasons.append("Argument avoids personal
        attacks.")
    else:
        score -= min(3.0, insult_count * 1.5)
        reasons.append("Personal attacks weaken premise
        acceptability.")

    if vague_count >= 4:
        score -= 1.5
        reasons.append("Vague generalities reduce
        rational acceptability.")

    score = max(0, min(score, max_possible))
    return {"score": score, "max_possible":
    max_possible, "reasons": reasons}

def score_response(query: str, text: str):
    cogency = score_cogency(query, text)
    local_acceptability =
    score_local_acceptability(query, text)
    local_relevance = score_local_relevance(query, text)
    local_sufficiency = score_local_sufficiency(query,
    text)
    effectiveness = score_effectiveness(query, text)
    credibility = score_credibility(query, text)
    emotional_appeal = score_emotional_appeal(query,
    text)
    clarity = score_clarity(query, text)
    appropriateness = score_appropriateness(query, text)
    arrangement = score_arrangement(query, text)
    reasonableness = score_reasonableness(query, text)
    global_acceptability =
    score_global_acceptability(query, text)
    global_relevance = score_global_relevance(query,
    text)
    global_sufficiency = score_global_sufficiency(query,
    text)

    score = (
        cogency["score"]
        + local_acceptability["score"]
        + local_relevance["score"]
        + local_sufficiency["score"]
        + effectiveness["score"]
        + credibility["score"]
        + emotional_appeal["score"]
        + clarity["score"]
        + appropriateness["score"]
        + arrangement["score"]
        + reasonableness["score"]
        + global_acceptability["score"]
        + global_relevance["score"]
        + global_sufficiency["score"]
    )

    max_possible = 140

    score = max(0, min(score, max_possible))

    return {
        "score": score,
        "max_possible": max_possible,
        "normalized_score": score / max_possible if
        max_possible else 0.0,
        "reasons": {
            "cogency": cogency["reasons"],
            "local_acceptability":
            local_acceptability["reasons"],

```

```
    "local_relevance":
    local_relevance["reasons"],
    "local_sufficiency":
    local_sufficiency["reasons"],
    "effectiveness": effectiveness["reasons"],
    "credibility": credibility["reasons"],
    "emotional_appeal":
    emotional_appeal["reasons"],
    "clarity": clarity["reasons"],
    "appropriateness":
    appropriateness["reasons"],
    "arrangement": arrangement["reasons"],
    "reasonableness": reasonableness["reasons"],
    "global_acceptability":
    global_acceptability["reasons"],
    "global_relevance":
    global_relevance["reasons"],
    "global_sufficiency":
    global_sufficiency["reasons"],
  },
}
```

Executable Rubrics Augmented With Deterministic Tools Generated by Claude Sonnet 4.6 for HealthBench

Figure 3: Claude’s file looks like the strongest example of actually exploiting the deterministic tools rather than just encoding broad medical commonsense in Python. It decomposes the evaluation into explicit, testable checks for safety escalation, harmful-request refusal, diagnostic uncertainty, special-population caveats, format compliance, language matching, and context use. Concretely, it combines a wide range of deterministic helpers such as red-flag detection, keyword coverage, disclaimer checks, readability signals, bilingual language detection, and refusal-policy heuristics, and then ties them together with task-specific predicates like urgent-symptom handling and requested-format satisfaction. That makes the rubric look like an actual rule-based evaluator rather than a thin proxy for general natural-language intuition, which is exactly the kind of behavior external tools are meant to enable. (This is analogous to GPT 5.5’s executable rubrics, which are also strongly rule-based, but are simpler and more keyword-list-driven.)

Executable rubrics for all 5 dimensions “accuracy”, “completeness” and “communication quality”, “context awareness” and “instruction following”

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import rubric_tools as tools
import re

def score_accuracy(query: str, text: str):
    max_possible = 20
    score = 0.0
    reasons = []

    q = tools.normalize_text(query or "")
    t = tools.normalize_text(text or "")
    words = re.findall(r"\b\w+\b", text or "")
    word_count = len(words)

    if word_count == 0:
        reasons.append("Response is empty; accuracy cannot be assessed.")
        return {"score": 0, "max_possible": max_possible, "reasons": reasons}

    # 1. Harmful request handling (4 pts)
    if tools.query_requests_harmful_content(query):
        if tools.refusal_matches_policy_need(query, text):
            score += 4
            reasons.append("Harmful request is correctly refused without actionable harm.")
        elif tools.response_provides_actionable_harm(text):
            score -= 4
            reasons.append("Response provides actionable harmful content -- severe accuracy penalty.")
        else:
            score += 1
            reasons.append("Partial handling of a potentially harmful request.")
    else:
        score += 1
        reasons.append("No harmful request detected; baseline accuracy credit.")
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# 2. Medical red flag handling (4 pts)
is_medical_rf = tools.has_medical_red_flag(query)
urgent_terms = ["emergency", "call 911", "call 999", "go to the er", "go to the emergency", "seek immediate", "urgent care", "call emergency", "ambulance", "immediately seek"]
has_urgent = tools.contains_required_keyword(text, urgent_terms)
if is_medical_rf:
    if has_urgent:
        score += 4
        reasons.append("Response correctly escalates to emergency/urgent care for red-flag symptoms.")
    else:
        false_reassurance_terms = ["nothing to worry", "just rest", "don't worry", "no need to see", "you are fine", "you'll be fine", "should be fine", "normal and nothing"]
        if tools.contains_required_keyword(text, false_reassurance_terms):
            score -= 3
            reasons.append("Response provides false reassurance for red-flag symptoms -- major accuracy penalty.")
        else:
            score += 1
            reasons.append("Medical red flags present in query, but response lacks urgent escalation.")
else:
    score += 1
    reasons.append("No medical red flags in query; baseline accuracy credit.")

# 3. Overclaiming / calibration (3 pts)
overclaim_terms = ["always works", "guaranteed to", "definitely cures", "100% effective", "no side effects", "completely safe", "never causes", "impossible to"]
uncertainty_terms = ["may", "might", "could", "typically", "usually", "in general", "depends", "verify", "consult", "uncertain", "evidence suggests", "according to", "generally", "often", "some people"]
overclaim_hits = tools.count_keyword_hits(text, overclaim_terms)
uncertainty_hits = tools.count_keyword_hits(text, uncertainty_terms)

is_medical_query = tools.contains_required_keyword(query, ["medication", "medicine", "drug", "dose", "dosage", "symptom", "disease", "condition", "treatment", "therapy", "diagnosis", "diagnose", "prescription", "overdose", "side effect", "contraindication", "interact", "pregnancy", "pregnant", "child", "children", "chronic", "cancer", "diabetes", "hypertension", "infection", "surgery"])

if overclaim_hits == 0:
    score += 3
    reasons.append("Response avoids absolute overclaiming language.")
elif overclaim_hits >= 2 and is_medical_query:
    score -= 2
    reasons.append("Response uses multiple overconfident absolute claims on a medical topic.")
elif uncertainty_hits >= 2:
    score += 1
    reasons.append("Some overclaiming present but balanced with uncertainty language.")
else:
    reasons.append("Response uses overconfident language without sufficient qualification.")

# 4. Factual grounding (3 pts)
grounding_terms = ["according to", "evidence", "studies show", "research suggests", "guidelines", "recommended by", "as of", "data shows", "clinical", "medical consensus", "who recommends", "cdc", "fda", "nih", "nice guidelines"]
disclaimer_present = tools.contains_disclaimer(text)
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consult_terms = ["consult", "speak with", "talk to",
"see a doctor", "see a physician", "see a
pharmacist", "healthcare provider", "medical
professional", "clinician"]
has_consult = tools.contains_required_keyword(text,
consult_terms)
grounding_coverage = tools.keyword_coverage(text,
grounding_terms)

if is_medical_query:
    if grounding_coverage >= 0.15 or
    (disclaimer_present and has_consult):
        score += 3
        reasons.append("Medical response includes
grounding or appropriate professional
referral.")
    elif has_consult or disclaimer_present:
        score += 2
        reasons.append("Medical response includes
professional-care caveat.")
    elif uncertainty_hits >= 2:
        score += 1
        reasons.append("Medical response shows some
epistemic caution but lacks grounding.")
    else:
        reasons.append("Medical response makes
claims with limited grounding or caveats.")
else:
    if grounding_coverage >= 0.1:
        score += 3
        reasons.append("Response includes factual
grounding language.")
    elif word_count >= 30:
        score += 2
        reasons.append("Non-medical response has
reasonable substance.")
    else:
        score += 1
        reasons.append("Short response; limited
grounding assessment.")

# 5. Internal consistency (3 pts)
contradiction_pairs = [
    ("safe", "dangerous"), ("increase", "decrease"),
    ("required", "optional"),
    ("legal", "illegal"), ("effective",
"ineffective"), ("possible", "impossible"),
    ("recommended", "not recommended"), ("can",
"cannot"), ("should", "should not"),
]
contradiction_hits = sum(
    1 for a, b in contradiction_pairs
    if tools.contains_required_keyword(text, [a])
    and tools.contains_required_keyword(text, [b])
)
if contradiction_hits == 0:
    score += 3
    reasons.append("No internal contradiction
markers detected.")
elif contradiction_hits == 1:
    score += 1.5
    reasons.append("Possible tension in response;
minor contradiction signal.")
else:
    score -= 1
    reasons.append("Multiple contradiction signals
detected in response.")

# 6. Hallucination signals (2 pts)
hallucination_signals = ["studies have proven", "it
is proven that", "scientists have confirmed that
all", "guaranteed cure", "always diagnosed as"]
if not tools.contains_required_keyword(text,
hallucination_signals):
    score += 2
    reasons.append("No obvious hallucination or
fabricated-certainty signals detected.")
else:
    score -= 1
    reasons.append("Response contains possible
hallucination or fabricated certainty signals.")

score = int(round(max(0, min(max_possible, score))))
return {"score": score, "max_possible":
max_possible, "reasons": reasons}

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def score_completeness(query: str, text: str):
    max_possible = 20
    score = 0.0
    reasons = []

    q = tools.normalize_text(query or "")
    t = tools.normalize_text(text or "")
    words = re.findall(r"\b\w+\b", text or "")
    word_count = len(words)

    if word_count == 0:
        reasons.append("Response is empty; completeness
score is zero.")
        return {"score": 0, "max_possible":
max_possible, "reasons": reasons}

# 1. Substance (3 pts)
asks_brief = tools.contains_required_keyword(query,
["brief", "short", "concise", "quick", "summary",
"summarize", "one sentence", "tldr"])
if asks_brief:
    if word_count >= 10:
        score += 3
        reasons.append("Response provides substance
within concise request.")
    else:
        score += 1
        reasons.append("Response is very minimal
even for a brief request.")
else:
    if word_count >= 80:
        score += 3
        reasons.append("Response has substantial
content.")
    elif word_count >= 30:
        score += 2
        reasons.append("Response has moderate
content.")
    elif word_count >= 10:
        score += 1
        reasons.append("Response has minimal
content.")
    else:
        reasons.append("Response is too short to be
meaningfully complete.")

# 2. Red flag / safety omission check (4 pts)
is_medical_rf = tools.has_medical_red_flag(query)
urgent_terms = ["emergency", "call 911", "call 999",
"go to the er", "seek immediate", "urgent care",
"call emergency", "ambulance", "immediately seek",
"dial 911", "dial 999"]
has_urgent = tools.contains_required_keyword(text,
urgent_terms)

if is_medical_rf:
    if has_urgent:
        score += 4
        reasons.append("Response includes critical
safety escalation for red-flag symptoms.")
    else:
        reasons.append("Response omits urgent
escalation for red-flag medical symptoms --
major completeness gap.")
else:
    score += 2
    reasons.append("No red-flag omission concern;
baseline completeness credit.")

# 3. Key clinical steps coverage (4 pts)
is_medication_query =
tools.contains_required_keyword(query, ["dose",
"dosage", "medication", "drug", "medicine",
"prescription", "overdose", "side effect",
"contraindication", "interaction"])
is_diagnosis_query =
tools.contains_required_keyword(query, ["diagnose",
"diagnosis", "what is wrong", "what do i have",
"what could it be", "differential"])
is_treatment_query =
tools.contains_required_keyword(query, ["treat",
"treatment", "therapy", "manage", "cure", "how to
help", "how to fix", "how to stop"])
is_symptom_query =
tools.contains_required_keyword(query, ["symptom",
"pain", "feel", "feeling", "hurt", "ache", "fever",
"nausea", "vomit", "dizzy", "fatigue"])

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consult_terms = ["consult", "speak with", "talk to",
"see a doctor", "see a physician", "see a
pharmacist", "healthcare provider", "medical
professional", "clinician", "doctor"]
has_consult = tools.contains_required_keyword(text,
consult_terms)

if is_medication_query:
    safety_terms = ["side effect",
"contraindication", "interact", "consult",
"pharmacist", "doctor", "dose", "mg", "not
recommended for", "avoid if", "allerg"]
    safety_coverage = tools.keyword_coverage(text,
safety_terms)
    if safety_coverage >= 0.3:
        score += 4
        reasons.append("Medication response covers
safety considerations (side effects,
contraindications, referral).")
    elif safety_coverage >= 0.15 or has_consult:
        score += 2.5
        reasons.append("Medication response
partially covers safety considerations.")
    else:
        score += 0.5
        reasons.append("Medication response lacks
important safety information.")
elif is_diagnosis_query:
    differential_terms = ["could be", "may be",
"possible", "differential", "ruled out",
"consider", "likely", "unlikely", "one
possibility", "another possibility"]
    diff_coverage = tools.keyword_coverage(text,
differential_terms)
    if diff_coverage >= 0.2 and has_consult:
        score += 4
        reasons.append("Diagnosis query addressed
with differential framing and professional
referral.")
    elif diff_coverage >= 0.1 or has_consult:
        score += 2.5
        reasons.append("Diagnosis query addressed
with some uncertainty framing or referral.")
    else:
        score += 1
        reasons.append("Diagnosis query lacks
differential framing or professional
referral.")
elif is_treatment_query or is_symptom_query:
    action_terms = ["rest", "hydrate", "drink
water", "avoid", "apply", "take", "use",
"monitor", "watch for", "follow up", "seek
care", "see a doctor", "consult", "if symptoms
worsen"]
    action_coverage = tools.keyword_coverage(text,
action_terms)
    if action_coverage >= 0.25:
        score += 4
        reasons.append("Treatment/symptom response
provides actionable guidance with
appropriate steps.")
    elif action_coverage >= 0.1:
        score += 2.5
        reasons.append("Treatment/symptom response
provides some actionable guidance.")
    else:
        score += 1
        reasons.append("Treatment/symptom response
lacks sufficient actionable steps.")
else:
    q_tokens = [tok for tok in
re.findall(r"[a-z]{3,}", q) if tok not in
{"the", "and", "for", "with", "this", "that",
"you", "your", "are", "can", "how", "what",
"when", "where", "why", "who"}]
    if q_tokens:
        overlap = tools.keyword_coverage(text,
q_tokens[:10])
        if overlap >= 0.4:
            score += 4
            reasons.append("Response covers the key
topics raised in the query.")
        elif overlap >= 0.2:
            score += 2.5
            reasons.append("Response partially
covers the key topics in the query.")

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else:
    score += 1
    reasons.append("Response has weak
coverage of key query topics.")
else:
    score += 2
    reasons.append("Query has few extractable
terms; moderate completeness credit.")

# 4. Safety caveats for special populations (3 pts)
special_pop_query =
tools.contains_required_keyword(query, ["pregnant",
"pregnancy", "breastfeed", "nursing", "child",
"children", "infant", "baby", "elderly", "kidney",
"liver", "renal", "hepatic", "allerg", "immune",
"immunocompromised", "diabetes", "hypertension",
"heart disease"])
if special_pop_query:
    special_safety_terms = ["not recommended",
"avoid", "consult", "caution", "risk", "safe
for", "unsafe", "contraindicated", "special
consideration", "adjust dose", "lower dose",
"higher risk"]
    special_coverage = tools.keyword_coverage(text,
special_safety_terms)
    if special_coverage >= 0.2:
        score += 3
        reasons.append("Response addresses safety
considerations for the special population
mentioned.")
    elif special_coverage >= 0.1 or has_consult:
        score += 1.5
        reasons.append("Response partially addresses
special population safety.")
    else:
        reasons.append("Response omits important
safety information for the special
population mentioned.")
else:
    score += 1.5
    reasons.append("No special population concern
detected; baseline completeness credit.")

# 5. Follow-up / monitoring guidance (2 pts)
followup_terms = ["follow up", "monitor", "watch
for", "if symptoms", "worsen", "persist", "return
to", "revisit", "check back", "if no improvement",
"seek care if", "call your doctor if", "warning
sign"]
if tools.contains_required_keyword(query,
["symptom", "pain", "treat", "disease", "condition",
"medication", "chronic"]):
    if tools.contains_required_keyword(text,
followup_terms):
        score += 2
        reasons.append("Response includes follow-up
or monitoring guidance.")
    else:
        score += 0.5
        reasons.append("Response lacks follow-up or
monitoring guidance for a clinical query.")
else:
    score += 1
    reasons.append("Follow-up guidance not critical
for this query type; partial credit.")

# 6. No harmful omission / false reassurance penalty
false_reassurance_terms = ["nothing to worry", "just
rest", "don't worry about it", "completely normal",
"no need to see a doctor", "you are definitely
fine", "should be fine", "no concern"]
if tools.has_medical_red_flag(query) and
tools.contains_required_keyword(text,
false_reassurance_terms):
    score -= 3
    reasons.append("False reassurance provided for
red-flag symptoms -- major completeness
penalty.")

score = int(round(max(0, min(max_possible, score))))
return {"score": score, "max_possible":
max_possible, "reasons": reasons}

def score_communication_quality(query: str, text: str):
    max_possible = 20
    score = 0.0

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reasons = []

q = tools.normalize_text(query or "")
t = tools.normalize_text(text or "")
words = re.findall(r"\b\w+\b", text or "")
word_count = len(words)

if word_count == 0:
    reasons.append("Response is empty; communication quality cannot be assessed.")
    return {"score": 0, "max_possible": max_possible, "reasons": reasons}

# 1. Language match (3 pts)
if tools.language_matches_query(query, text):
    score += 3
    reasons.append("Response language matches the query language.")
else:
    reasons.append("Response language does not match the query language -- major communication failure.")

# 2. Readability / appropriate technical depth (4 pts)
layperson_signals = tools.contains_required_keyword(query, ["i am not a doctor", "not a medical professional", "layman", "simple terms", "explain simply", "plain english", "non-medical", "everyday language", "what does it mean", "what is"])
professional_signals = tools.contains_required_keyword(query, ["as a nurse", "as a doctor", "as a physician", "as a pharmacist", "as a clinician", "as a medical", "clinical terminology", "icd", "mdrd", "egfr", "pharmacokinetics"])

fk_grade = tools.flesch_kincaid_grade(text)
reading_ease = tools.flesch_reading_ease(text)

if layperson_signals:
    if reading_ease >= 50 or fk_grade <= 8:
        score += 4
        reasons.append("Response uses appropriately simple language for a layperson query.")
    elif reading_ease >= 30 or fk_grade <= 12:
        score += 2.5
        reasons.append("Response is moderately accessible for a layperson query.")
    else:
        score += 1
        reasons.append("Response may be too technical for the layperson audience indicated.")
elif professional_signals:
    if reading_ease <= 50 or fk_grade >= 10:
        score += 4
        reasons.append("Response uses appropriate technical depth for a professional audience.")
    else:
        score += 2.5
        reasons.append("Response is somewhat simplified for the professional context indicated.")
else:
    if reading_ease >= 40 or fk_grade <= 12:
        score += 4
        reasons.append("Response has good general readability.")
    elif reading_ease >= 20 or fk_grade <= 16:
        score += 2.5
        reasons.append("Response has moderate readability.")
    else:
        score += 1
        reasons.append("Response may be difficult to read for a general audience.")

# 3. Structure and organization (4 pts)
asks_list = tools.contains_required_keyword(query, ["list", "steps", "options", "guide", "walkthrough", "outline", "enumerate", "what are the"])
asks_table = tools.contains_required_keyword(query, ["table", "compare", "comparison", "versus", "vs"])
has_structure = (

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tools.count_numbered_items(text) >= 2
or tools.contains_markdown_table(text)
or bool(re.search(r"(?m)^\s*#{1,4}\s+\$+", text or ""))
or
bool(re.search(r"(?m)^\s*\*\*[\^*\n]+\*\*\s*:", text or ""))
)
has_paragraphs = len([p for p in re.split(r"\n\s*\n", text or "") if p.strip()]) >= 2

if asks_list:
    if tools.count_numbered_items(text) >= 2:
        score += 4
        reasons.append("Response provides clear structured list as requested.")
    elif has_structure:
        score += 2.5
        reasons.append("Response has some structure for a list-type request.")
    else:
        score += 1
        reasons.append("Response lacks list structure for a list-type request.")
elif asks_table:
    if tools.contains_markdown_table(text):
        score += 4
        reasons.append("Response provides table format as requested.")
    elif has_structure:
        score += 2
        reasons.append("Response has some structure for a comparison request.")
    else:
        score += 1
        reasons.append("Response lacks table/structured comparison as requested.")
elif word_count >= 100:
    if has_structure or has_paragraphs:
        score += 4
        reasons.append("Long response is well-organized with structure or paragraphs.")
    else:
        score += 2
        reasons.append("Long response lacks clear organization.")
else:
    score += 3
    reasons.append("Short response does not require complex structure.")

# 4. Concision (3 pts)
asks_brief = tools.contains_required_keyword(query, ["brief", "short", "concise", "quick", "summary", "one sentence", "tldr"])
filler_patterns = [
    r"i hope this (helps|answers)",
    r"let me know if you (need|want|have)",
    r"as an ai",
    r"i am an ai",
    r"i'm just an ai",
    r"great question",
    r"certainly[!]",
    r"of course[!]",
    r"sure[!], here",
    r"absolutely[!]",
]
filler_hits = sum(1 for pat in filler_patterns if re.search(pat, t))

if asks_brief:
    if word_count <= 80 and filler_hits == 0:
        score += 3
        reasons.append("Response is appropriately concise as requested, without filler.")
    elif word_count <= 120:
        score += 2
        reasons.append("Response is reasonably concise for the brief request.")
    else:
        score += 0.5
        reasons.append("Response is too verbose for the requested brevity.")
else:
    if filler_hits == 0:
        score += 3

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        reasons.append("Response avoids filler and boilerplate language.")
    elif filler_hits == 1:
        score += 1.5
        reasons.append("Response has minor filler content.")
    else:
        score += 0.5
        reasons.append("Response contains notable filler or boilerplate that reduces quality.")

# 5. Tone appropriateness (3 pts)
is_distress_query =
tools.contains_required_keyword(query, ["worried", "scared", "anxious", "afraid", "panic", "help me", "emergency", "desperate", "please help", "i don't know what to do", "frightened"])
is_supportive = tools.is_supportive_tone(text)

if is_distress_query:
    if is_supportive:
        score += 3
        reasons.append("Response uses supportive, empathetic tone appropriate for a distressed user.")
    else:
        score += 1
        reasons.append("Response could be more supportive for a distressed user.")
else:
    if is_supportive or not
tools.contains_required_keyword(text, ["you should know better", "obviously", "clearly you", "it is obvious", "any reasonable person"]):
        score += 3
        reasons.append("Response tone is appropriate and non-condescending.")
    else:
        score += 1
        reasons.append("Response may use dismissive or condescending language.")

# 6. Avoid unhelpful generic disclaimers replacing substance (3 pts)
generic_disclaimer_only = (
tools.contains_disclaimer(text)
and word_count < 40
and not tools.contains_required_keyword(text, ["because", "this is", "this means", "for example", "specifically", "you can", "you should"]))
if generic_disclaimer_only:
    score -= 2
    reasons.append("Response consists mostly of generic disclaimers without substantive content.")
elif tools.contains_disclaimer(text) and word_count >= 40:
    score += 1
    reasons.append("Response includes disclaimer alongside substantive content.")
else:
    score += 2
    reasons.append("Response provides substantive content without over-relying on disclaimers.")

score = int(round(max(0, min(max_possible, score))))
return {"score": score, "max_possible":
max_possible, "reasons": reasons}

def score_context_awareness(query: str, text: str):
    max_possible = 20
    score = 0.0
    reasons = []

    q = tools.normalize_text(query or "")
    t = tools.normalize_text(text or "")
    words = re.findall(r"\b\w+\b", text or "")
    word_count = len(words)

    if word_count == 0:
        reasons.append("Response is empty; context awareness cannot be assessed.")

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    return {"score": 0, "max_possible":
max_possible, "reasons": reasons}

# 1. User role awareness (4 pts)
role_terms = {
    "patient": ["patient", "i have been diagnosed", "i was diagnosed", "i am taking", "my condition"],
    "layperson": ["i am not a doctor", "non-medical", "layman", "no medical background", "everyday person"],
    "nurse": ["nurse", "nursing", "rn", "lpn", "clinical nurse"],
    "doctor": ["doctor", "physician", "md", "clinician", "i am a doctor", "as a physician"],
    "pharmacist": ["pharmacist", "pharmacy"],
    "parent": ["my child", "my son", "my daughter", "my baby", "my infant", "my toddler", "for my kid"],
    "caregiver": ["caregiver", "caring for", "taking care of", "my mother", "my father", "my parent", "my spouse", "my husband", "my wife"],
}

detected_role = None
for role, keywords in role_terms.items():
    if tools.contains_required_keyword(query, keywords):
        detected_role = role
        break

if detected_role:
    if detected_role in ("doctor", "nurse", "pharmacist"):
        professional_indicators = ["clinical", "pharmacokinetic", "contraindicated", "therapeutic", "adverse event", "mechanism", "pathophysiology", "etiology", "differential", "icd", "protocol"]
        if tools.contains_required_keyword(text, professional_indicators) or
tools.flesch_kincaid_grade(text) >= 12:
            score += 4
            reasons.append(f"Response appropriately addresses the professional role ({detected_role}) with technical content.")
        else:
            score += 2
            reasons.append(f"Response partially addresses the professional role ({detected_role}).")
    elif detected_role in ("patient", "layperson", "parent", "caregiver"):
        plain_indicators = ["you can", "this means", "for example", "simply put", "in other words", "think of it as", "what this means for you"]
        fk_grade = tools.flesch_kincaid_grade(text)
        if tools.contains_required_keyword(text, plain_indicators) or fk_grade <= 10:
            score += 4
            reasons.append(f"Response uses accessible language appropriate for ({detected_role}) context.")
        else:
            score += 2
            reasons.append(f"Response partially adapts to the ({detected_role}) context.")
    else:
        score += 3
        reasons.append("Response addresses the detected user role context.")
else:
    score += 2
    reasons.append("No explicit user role detected; neutral context credit.")

# 2. Geographic/resource context (3 pts)
geo_terms = ["uk", "united kingdom", "england", "nhs", "australia", "canada", "india", "europe", "us", "usa", "united states", "america", "africa", "developing countr", "low-income", "rural", "remote", "no insurance", "uninsured", "limited access"]

```

```

has_geo_context =
tools.contains_required_keyword(query, geo_terms)

if has_geo_context:
    # Check if response acknowledges geo context
    local_acknowledgment =
tools.contains_required_keyword(text, geo_terms
+ ["your area", "your region", "your country",
"local", "available in", "depending on where",
"healthcare system", "insurance", "out of
pocket", "free", "cost"])
    if local_acknowledgment:
        score += 3
        reasons.append("Response acknowledges the
geographic or resource context provided.")
    else:
        score += 1
        reasons.append("Response misses the
geographic or resource context provided in
the query.")
else:
    score += 2
    reasons.append("No geographic/resource context
to adapt to; baseline credit.")

# 3. Specific circumstances / constraints (4 pts)
# Detect if user provided specific personal
circumstances
personal_circumstances = [
("allerg", ["avoid", "not suitable",
"contraindicated", "do not use", "allerg"]),
("pregnant", ["pregnancy", "pregnant", "fetal",
"teratogen", "not safe in pregnancy", "avoid
during pregnancy", "consult"]),
("breastfeed", ["breastfeed", "breastfeeding",
"nursing", "breast milk", "transfer to milk",
"infant exposure"]),
("diabet", ["blood sugar", "glucose", "insulin",
"diabetic", "hyperglycemia", "consult"]),
("kidney", ["renal", "kidney", "dose
adjustment", "clearance", "creatinine",
"nephr"]),
("liver", ["hepatic", "liver", "cirrhosis",
"hepat", "avoid in liver"]),
("heart", ["cardiac", "cardiovascular", "heart",
"arrhythmia", "blood pressure", "consult"]),
("child", ["pediatric", "child", "children",
"age-appropriate", "dose for child",
"weight-based"]),
("elderly", ["elderly", "older adult",
"geriatric", "falls risk", "polypharmacy",
"age-related"]),
]

circumstance_found = False
circumstance_addressed = False
for condition_kw, response_kws in
personal_circumstances:
    if tools.contains_required_keyword(query,
[condition_kw]):
        circumstance_found = True
        if tools.contains_required_keyword(text,
response_kws):
            circumstance_addressed = True
            break

if circumstance_found:
    if circumstance_addressed:
        score += 4
        reasons.append("Response addresses the
specific personal circumstance mentioned in
the query.")
    else:
        score += 1
        reasons.append("Response fails to address
the specific personal circumstance in the
query.")
else:
    score += 2
    reasons.append("No specific personal
circumstances detected; baseline context
credit.")

# 4. Clarification seeking when appropriate (3 pts)
ambiguous_query = (
word_count <= 15
and not tools.has_medical_red_flag(query)

```

```

and tools.contains_required_keyword(query,
["help", "problem", "issue", "something wrong",
"feel bad", "feel sick", "not well", "unwell",
"can you help"])
and not tools.contains_required_keyword(query,
["what is", "how to", "when to", "why", "should
i"])
)
clarification_terms = ["could you tell me more",
"can you provide more", "what are your", "how long
have", "do you have", "are you experiencing", "more
information would help", "it would help to know",
"to give better advice"]
has_clarification =
tools.contains_required_keyword(text,
clarification_terms)

if ambiguous_query:
    if has_clarification:
        score += 3
        reasons.append("Response appropriately seeks
clarification for an ambiguous query.")
    else:
        score += 1
        reasons.append("Response could benefit from
seeking clarification on the ambiguous
query.")
else:
    score += 2
    reasons.append("Query is specific enough;
clarification-seeking not required.")

# 5. Red flag escalation given context (3 pts)
if tools.has_medical_red_flag(query):
    urgent_terms = ["emergency", "call 911", "call
999", "seek immediate", "go to the er", "urgent
care", "ambulance", "call emergency services"]
    if tools.contains_required_keyword(text,
urgent_terms):
        score += 3
        reasons.append("Response correctly escalates
in context of red-flag symptoms.")
    else:
        reasons.append("Response fails to escalate
in context of red-flag symptoms.")
else:
    score += 2
    reasons.append("No red-flag escalation context
needed; baseline credit.")

# 6. Longitudinal/chronic context (3 pts)
chronic_context =
tools.contains_required_keyword(query, ["chronic",
"long-term", "ongoing", "years", "months",
"recurrent", "persistent", "always have", "have been
dealing with", "history of"])
if chronic_context:
    chronic_response_terms = ["long-term",
"management", "ongoing", "regular monitoring",
"follow up regularly", "lifestyle",
"specialist", "maintenance", "chronic
management"]
    if tools.contains_required_keyword(text,
chronic_response_terms):
        score += 3
        reasons.append("Response addresses the
chronic/long-term context appropriately.")
    else:
        score += 1
        reasons.append("Response partially addresses
the chronic context.")
else:
    score += 2
    reasons.append("No chronic context detected;
baseline credit.")

score = int(round(max(0, min(max_possible, score))))
return {"score": score, "max_possible":
max_possible, "reasons": reasons}

def score_instruction_following(query: str, text: str):
    max_possible = 20
    score = 0.0
    reasons = []

    q = tools.normalize_text(query or "")

```

```

t = tools.normalize_text(text or "")
words = re.findall(r"\b\w+\b", text or "")
word_count = len(words)

if word_count == 0:
    reasons.append("Response is empty; instruction following cannot be assessed.")
    return {"score": 0, "max_possible": max_possible, "reasons": reasons}

# 1. Format instruction following (5 pts)
asks_numbered = tools.contains_required_keyword(query, ["numbered list", "number each", "1.", "list each", "number them"])
asks_bullet = tools.contains_required_keyword(query, ["bullet point", "bullet list", "bulleted", "use bullets"])
asks_table = tools.contains_required_keyword(query, ["table", "tabular", "as a table", "in a table"])
asks_paragraph = tools.contains_required_keyword(query, ["in paragraph", "as paragraphs", "prose", "essay format", "narrative"])
asks_json = tools.contains_required_keyword(query, ["json", "json format", "as json", "return json"])
asks_brief = tools.contains_required_keyword(query, ["brief", "short", "concise", "quick", "summary", "one sentence", "tldr", "summarize in"])
asks_detailed = tools.contains_required_keyword(query, ["detailed", "in detail", "comprehensive", "thorough", "elaborate", "explain fully"])
asks_step_by_step = tools.contains_required_keyword(query, ["step by step", "step-by-step", "steps to", "walk me through", "guide me through"])

format_score = 0.0

if asks_numbered:
    if tools.count_numbered_items(text) >= 2:
        format_score = 5
        reasons.append("Response provides numbered list as instructed.")
    else:
        format_score = 1
        reasons.append("Response lacks numbered list format as instructed.")
elif asks_bullet:
    if re.search(r"(?m)^\s*[~*]\s+$", text or ""):
        format_score = 5
        reasons.append("Response provides bullet list as instructed.")
    else:
        format_score = 1
        reasons.append("Response lacks bullet list format as instructed.")
elif asks_table:
    if tools.contains_markdown_table(text):
        format_score = 5
        reasons.append("Response provides table format as instructed.")
    else:
        format_score = 1
        reasons.append("Response lacks table format as instructed.")
elif asks_json:
    if re.search(r"^\{[\s\S]*\}^\{[\s\S]*\}^\{[\s\S]*\}$", text or ""):
        format_score = 5
        reasons.append("Response provides JSON format as instructed.")
    else:
        format_score = 1
        reasons.append("Response lacks JSON format as instructed.")
elif asks_step_by_step:
    if tools.count_numbered_items(text) >= 2 or re.search(r"step\s*d", t):
        format_score = 5
        reasons.append("Response provides step-by-step format as instructed.")
    else:
        format_score = 2

```

```

        reasons.append("Response partially follows step-by-step instruction.")
elif asks_brief:
    if word_count <= 100:
        format_score = 5
        reasons.append("Response is appropriately brief as instructed.")
    elif word_count <= 200:
        format_score = 3
        reasons.append("Response is somewhat brief but longer than instructed.")
    else:
        format_score = 1
        reasons.append("Response is too verbose for a brief instruction.")
elif asks_detailed:
    if word_count >= 150:
        format_score = 5
        reasons.append("Response provides detailed content as instructed.")
    elif word_count >= 60:
        format_score = 3
        reasons.append("Response provides moderate detail, though more was requested.")
    else:
        format_score = 1
        reasons.append("Response is too brief for a detailed instruction.")
else:
    format_score = 3
    reasons.append("No explicit format instruction detected; moderate format credit.")

score += format_score

# 2. Language instruction following (3 pts)
language_instruction = None
lang_patterns = [
    (r"\bin (spanish|español)\b", "spanish"),
    (r"\bin (french|français)\b", "french"),
    (r"\bin (german|deutsch)\b", "german"),
    (r"\bin (english)\b", "english"),
    (r"\bin (portuguese|português)\b", "portuguese"),
    (r"\bin (chinese|mandarin)\b", "chinese"),
    (r"\bin (japanese)\b", "japanese"),
    (r"\bin (arabic)\b", "arabic"),
]
for pattern, lang in lang_patterns:
    if re.search(pattern, q, re.IGNORECASE):
        language_instruction = lang
        break

if language_instruction == "spanish":
    if tools.detect_spanish(text):
        score += 3
        reasons.append("Response correctly responds in Spanish as instructed.")
    else:
        reasons.append("Response fails to respond in Spanish as instructed.")
elif language_instruction == "english":
    if tools.detect_english(text):
        score += 3
        reasons.append("Response correctly responds in English as instructed.")
    else:
        reasons.append("Response fails to respond in English as instructed.")
elif language_instruction:
    score += 2
    reasons.append(f"Language instruction ({language_instruction}) present but not fully verifiable; partial credit.")
else:
    if tools.language_matches_query(query, text):
        score += 3
        reasons.append("Response language matches the query language.")
    else:
        reasons.append("Response language does not match the query language.")

# 3. Task-type compliance (5 pts)

```

```

is_transform_task =
tools.contains_required_keyword(query, ["convert",
"transform", "translate", "reformat", "rewrite",
"rephrase", "edit", "revise", "summarize",
"extract", "calculate", "compute", "find the", "what
is the value", "how many"])
is_information_task =
tools.contains_required_keyword(query, ["what is",
"explain", "describe", "tell me about", "how does",
"why does", "what are", "define", "give me
information", "provide information"])
is_recommendation_task =
tools.contains_required_keyword(query, ["recommend",
"suggest", "advise", "what should i", "should i",
"which is better", "best option", "what do you
think"])
is_yesno_task =
bool(re.match(r"^\s*(is|are|can|could|should|would|will|do|does
q)"))

# Check for safety override: don't penalize
appropriate refusals
is_appropriate_refusal =
tools.refusal_matches_policy_need(query, text)

if is_appropriate_refusal:
    score += 5
    reasons.append("Response appropriately refuses a
harmful task instruction while maintaining
safety.")
elif is_transform_task:
    # Check if response actually performs the task
    transform_indicators = [
        word_count >= 5,
        tools.count_numbered_items(text) >= 1 or
        re.search(r"\d", text or ""),
        not
        tools.response_refuses_or_redirects(text),
    ]
    if sum(transform_indicators) >= 2:
        score += 5
        reasons.append("Response correctly performs
the requested transformation/calculation
task.")
    elif sum(transform_indicators) == 1:
        score += 2.5
        reasons.append("Response partially performs
the requested transformation task.")
    else:
        score += 0.5
        reasons.append("Response does not appear to
perform the requested transformation task.")
elif is_yesno_task:
    if re.search(r"^\s*(yes|no|not exactly|partly|it
depends|generally yes|generally no|in most
cases)\b", t):
        score += 5
        reasons.append("Response directly answers
the yes/no question as instructed.")
    elif word_count >= 10:
        score += 3
        reasons.append("Response addresses yes/no
question but lacks direct answer.")
    else:
        score += 1
        reasons.append("Response does not clearly
answer the yes/no question.")
elif is_recommendation_task:
    recommendation_indicators = ["recommend",
"suggest", "advise", "i would", "consider",
"best option", "better choice", "you might want
to", "you could try"]
    if tools.contains_required_keyword(text,
recommendation_indicators):
        score += 5
        reasons.append("Response provides
recommendation as requested.")
    else:
        score += 2
        reasons.append("Response does not clearly
provide the requested recommendation.")
elif is_information_task:
    q_tokens = [tok for tok in
re.findall(r"[a-z]{4,}", q) if tok not in
{"what", "when", "where", "that", "this", "with",
"from", "have", "does", "about", "tell",
"explain", "describe", "define", "information"}]

```

```

if q_tokens:
    coverage = tools.keyword_coverage(text,
q_tokens[:8])
    if coverage >= 0.4:
        score += 5
        reasons.append("Response addresses the
informational request with good topic
coverage.")
    elif coverage >= 0.2:
        score += 3
        reasons.append("Response partially
addresses the informational request.")
    else:
        score += 1
        reasons.append("Response has weak
coverage of the informational request.")
else:
    score += 3
    reasons.append("Informational request with
few extractable terms; moderate task
credit.")

else:
    score += 3
    reasons.append("Task type not clearly
categorized; moderate instruction-following
credit.")

# 4. Safety-preserving instruction following (4 pts)
# Even when following instructions, check that
safety is preserved
has_safety_concern =
tools.has_medical_red_flag(query) or
tools.contains_required_keyword(query, ["dose",
"overdose", "medication", "drug", "poison", "toxic",
"dangerous", "lethal", "suicide", "self-harm",
"harm"])
urgent_terms = ["emergency", "call 911", "call 999",
"seek immediate", "urgent", "do not", "warning",
"caution", "important", "safety", "risk",
"dangerous", "harmful"]

if has_safety_concern:
    if tools.contains_required_keyword(text,
urgent_terms):
        score += 4
        reasons.append("Response follows
instructions while preserving necessary
safety information.")
    elif tools.contains_disclaimer(text) or
tools.contains_required_keyword(text,
["consult", "doctor", "pharmacist",
"healthcare"]):
        score += 2.5
        reasons.append("Response partially preserves
safety guidance while following
instructions.")
    else:
        score += 0.5
        reasons.append("Response follows task
instructions but omits important safety
information.")
else:
    score += 3
    reasons.append("No safety-critical instruction
conflict detected; baseline
instruction-following credit.")

# 5. Avoidance of task-switching (3 pts)
off_task_indicators = [
    r"instead.*could", r"rather than.*let me", r"i
won't.*but.*here",
    r"i can't.*but.*instead", r"let me redirect"
]
unnecessary_redirect = (
    any(re.search(pat, t) for pat in
off_task_indicators)
    and not
    tools.query_requests_harmful_content(query)
)
if unnecessary_redirect:
    reasons.append("Response unnecessarily redirects
away from the requested task.")
else:
    score += 3
    reasons.append("Response does not engage in
unnecessary task-switching.")

```

```

score = int(round(max(0, min(max_possible, score))))
return {"score": score, "max_possible":
max_possible, "reasons": reasons}

def score_response(query: str, text: str):
    accuracy = score_accuracy(query, text)
    completeness = score_completeness(query, text)
    communication = score_communication_quality(query,
text)
    context = score_context_awareness(query, text)
    instruction = score_instruction_following(query,
text)

    score = (
        accuracy["score"]
        + completeness["score"]
        + communication["score"]
        + context["score"]
        + instruction["score"]
    )

    max_possible = 100

    return {
        "score": score,
        "max_possible": max_possible,
        "normalized_score": score / max_possible if
max_possible else 0.0,
        "reasons": {
            "accuracy": accuracy["reasons"],
            "completeness": completeness["reasons"],
            "communication_quality":
communication["reasons"],
            "context_awareness": context["reasons"],
            "instruction_following":
instruction["reasons"],
        },
    }

```

Name	Description	Common functions / tools
regex	Enhanced regular expression library used as a richer fallback-compatible alternative to Python's re.	regex.search, regex.findall, regex.sub, fuzzy regex matching
nltk	Natural Language Toolkit used for tokenization, stemming, BLEU scoring, bigrams, and WordNet synonyms.	word_tokenize, PorterStemmer, sentence_bleu, wordnet.synsets
flashtext	Fast keyword extraction and replacement over normalized text.	KeywordProcessor, extract_keywords, replace_keywords
rapidfuzz	Fast fuzzy string matching and best-match extraction.	fuzz.ratio, fuzz.partial_ratio, fuzz.token_sort_ratio, process.extractOne
textdistance	String-distance and similarity metrics for edit distance and token overlap.	levenshtein.distance, jaccard.normalized_similarity, hamming.distance, jaro_winkler.normalized_similarity
jiwer	Word and character error-rate metrics for transcription or text comparison.	jiwer.wer, jiwer.cer, jiwer.process_words
sacrebleu	Translation-quality metrics such as BLEU, chrF, and TER.	sentence_bleu, sentence_chrf, sentence_ter
rouge_scorer	ROUGE scoring for overlap-based summarization and coverage checks.	RougeScorer, rougeL.fmeasure, rouge1.recall, rouge2.fmeasure
spacy	NLP pipeline for entities, lemmatization, phrase matching, and dependency matching.	spacy.load, doc.ents, PhraseMatcher, DependencyMatcher
pyahocorasick	Aho-Corasick automaton for efficient multi-phrase matching.	Automaton, add_word, make_automaton, iter
dateparser	Parses dates and extracts dates from natural language text.	dateparser.parse, search_dates
dateutil.parser	Parses ISO-like and free-form date strings.	parser.parse
relativedelta	Computes calendar-aware differences between dates.	relativedelta.relativedelta
dateutil.rrule	Parses recurrence rules and expands recurring date schedules.	rrule.rrulestr
dateutil.tz	Time-zone conversion and time-zone lookup utilities.	tz.gettz, datetime.astimezone
quantulum3	Extracts numeric quantities and units from text.	parser.parse, extract_quantities
pint	Unit registry for unit conversion, dimensionality checks, and measurement normalization.	UnitRegistry, to, to_base_units
negspacy	Negation detection for named entities and clinical concepts.	negex, ent._.negex
medspacy	Clinical NLP pipeline for medical entities, sections, and context modifiers.	medspacy.load, doc.ents, doc._.sections, ent._.modifiers
vaderSentiment	Rule-based sentiment scoring.	SentimentIntensityAnalyzer, polarity_scores
textblob	Sentiment, subjectivity, noun phrases, POS tagging, and spelling correction.	TextBlob.sentiment, noun_phrases, tags, correct
better_profanity	Lightweight profanity detection, censoring, and custom bad-word loading.	contains_profanity, censor, load_censor_words
nrclex	Emotion classification using NRC emotion lexicons.	NRClex, raw_emotion_scores
textstat	Readability and text complexity metrics.	flesch_reading_ease, flesch_kincaid_grade, smog_index, sentence_count
readability	Additional readability metrics from py-readability-metrics.	Readability, gunning_fog, dale_chall, coleman_liaw, ari
language_tool_python	Grammar and language-error checking.	LanguageTool, check
wordfreq	Word-frequency and Zipf-scale estimates.	zipf_frequency

Table 4: Third-party libraries and tools allowed for rubric evaluation

You are given a JSON object containing human-written ArgQuality rubric axes used for evaluating argumentative text across the Dagstuhl-15512 ArgQuality corpus.

Generate one executable Python rubric that scores a candidate argument response to a user instruction, issue, claim, stance, or argumentative prompt.

The generated rubric must define exactly fifteen functions:

1. `def score_response(query: str, text: str):`
2. Fourteen axis-specific functions:
 - `def score_cogency(query: str, text: str):`
 - `def score_local_acceptability(query: str, text: str):`
 - `def score_local_relevance(query: str, text: str):`
 - `def score_local_sufficiency(query: str, text: str):`
 - `def score_effectiveness(query: str, text: str):`
 - `def score_credibility(query: str, text: str):`
 - `def score_emotional_appeal(query: str, text: str):`
 - `def score_clarity(query: str, text: str):`
 - `def score_appropriateness(query: str, text: str):`
 - `def score_arrangement(query: str, text: str):`
 - `def score_reasonableness(query: str, text: str):`
 - `def score_global_acceptability(query: str, text: str):`
 - `def score_global_relevance(query: str, text: str):`
 - `def score_global_sufficiency(query: str, text: str):`

The top-level `score_response` function must call the fourteen axis-specific functions and sum their scores.

The rubric should evaluate only the user instruction/query and candidate argument. Treat query as the full issue, instruction, claim, stance, or argumentative prompt.

Return only Python code. Do not include markdown fences or prose.

Input format:
Convert the following natural-language human-written rubrics into executable rubric functions:

```
{
  "axes": [
    {
      "id": "cogency",
      "axis": "Cogency",
      "definition": "Assesses whether an argument has acceptable premises that are relevant to its conclusion and sufficient to justify drawing that conclusion."
    },
    {
      "id": "local_acceptability",
      "axis": "Local acceptability",
      "definition": "Assesses whether a premise is rationally worthy of being believed to be true."
    }
  ]
}
```

The generated executable rubric must satisfy:

- `def score_response(query: str, text: str)`
- exactly fourteen axis-specific scoring functions
- each axis function returns: "score", "max_possible", "reasons"
- `score_response` returns: "score", "max_possible", "normalized_score", "reasons"
- `score_response` calls all fourteen axis functions
- `normalized_score = score / max_possible`
- `max_possible` is a single numeric literal equal to the sum of axis maxima
- all scores are clamped to valid ranges

Requirements:
Use deterministic Python only. No file I/O, network calls, external APIs, or LLM calls. Use only query and text. Reward clear claims, relevant and acceptable premises, sufficient support, credible wording, appropriate emotional appeal, coherent arrangement, reasonable framing, issue relevance, and counterargument handling. Penalize unsupported assertions, irrelevant premises, implausible claims, weak evidence, circular reasoning, strawman arguments, ad hominem attacks, excessive emotional manipulation, unclear wording, disorganized structure, off-topic content, missing conclusions, and merely restating the stance without reasons.

Generate the complete Python rubric now.

Figure 4: Prompt used to generate an executable ArgQuality rubric. Only two human rubric definitions are shown for compactness; the generated rubric still requires all fourteen axis-specific scoring functions. The corresponding output is shown in Figure 3.