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Assessing Large Language Models on Climate Information

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Abstract

As Large Language Models (LLMs) rise in popularity, it is necessary to assess their capability in critically relevant domains. We present a comprehensive evaluation framework, grounded in science communication research, to assess LLM responses to questions about climate change. Our framework emphasizes both presentational and epistemological adequacy, offering a fine-grained analysis of LLM generations spanning 8 dimensions and 30 issues. Our evaluation task is a real-world example of a growing number of challenging problems where AI can complement and lift human performance. We introduce a novel protocol for scalable oversight that relies on AI Assistance and raters with relevant education. We evaluate several recent LLMs on a set of diverse climate questions. Our results point to a significant gap between surface and epistemological qualities of LLMs in the realm of climate communication.

1. Introduction

As concerns around *climate change* intensify (Poushter et al., 2022; WHO, 2021), more and more people turn to digital media as their primary source of information (Newman et al., 2021). However, in spite of ubiquitous access to information, there remains a considerable gap in climate literacy, exacerbated by the spread of mis- and disinformation (Leiserowitz et al., 2022). The challenge of conveying climate data arises also from the nature of scientific communication: science, as an evolving domain, is laden with specialized knowledge, complexity, and inherent uncertainties (Moser, 2016). The digital media landscape, characterized by soaring amounts of AI-generated content (Thompson et al., 2024), limited attention spans and adversarial dynamics, further compounds these challenges (Pearce et al., 2019).

While AI's promise in addressing global climate challenges is evident through its applications in climate modeling, energy optimization, and disaster management (Rolnick et al., 2022), its intersection with Natural Language Processing (NLP) is still under-explored. Given recent advancements in LLMs (Brown et al., 2020; Chowdhery et al., 2022; OpenAI, 2023; Gemini Team, 2023) there is hope that generative AI will also help addressing climate information challenges. However, using LLMs to address science-related information raises factuality concerns (Weidinger et al., 2021). Eloquence and advanced dialogue behaviors are trusted by users, even in the absence of trustworthy information (Chiesurin et al., 2023). This makes evaluating LLMs difficult. Research on evaluating systems that may achieve or exceed human abilities, or *scalable oversight* (Amodei et al., 2016) is so far mostly theoretical (Irving et al., 2018; Leike et al., 2018; Christiano et al., 2018), with some recent more practical advances (Michael et al., 2023).

We introduce a framework based on Science Communication research (Jamieson et al., 2017), to begin evaluating LLMs' responses within the climate change context in a principled way.[1] The evaluation relies on raters with relevant educational background. We assess **presentational** properties such as *style*, *clarity*, linguistic *correctness*, and *tone*. More importantly, we also assess **epistemological** issues: *accuracy*, *specificity*, *completeness*, and *uncertainty*. To test the relevance of the evaluation, we run an empirical study on a diverse set of 300 climate change-related questions involving some of the most recent and prominent LLMs.

Our main findings are as follows:

- To increase the recall of detected issues and improve rating quality, it is crucial to introduce scalable oversight protocols that use grounded AI Assistance (cf. Figure 1). However, while AI assistance demonstrably

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[1]To aid reproducibility, we provide the exact evaluation protocols and all prompts used to generate data.

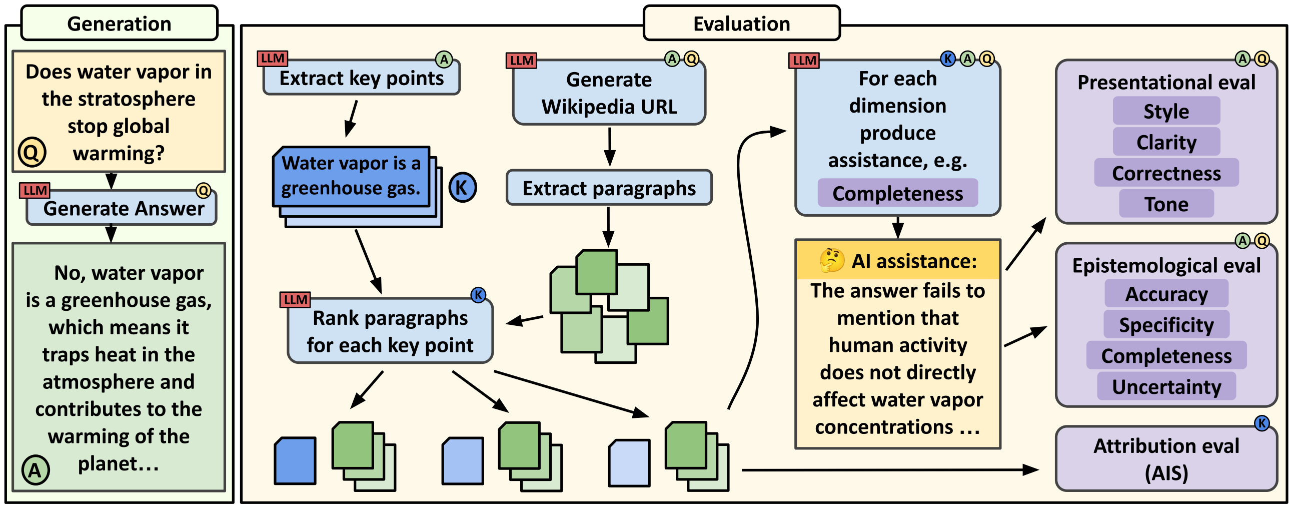

Figure 1. Overview of the evaluation pipeline as described in Section 3. Starting with a question-answer pair, we use an LLM to extract key points from the answer. We also use the LLM to find a relevant Wikipedia page from which we extract paragraphs. For each key point we rank the paragraphs and keep the top ones. We combine all this information to generate AI assistance for each of our evaluation dimensions. Presentational dimensions are evaluated without the additional paragraphs. This assistance, if available, is presented to our human raters along with the answer. Note that the raters for presentational and epistemological dimension are not shown the key points or retrieved paragraphs. We however use the key points and paragraphs evaluate attribution, cf. Appendix A.12.

improves rating quality, its influence on raters extends beyond this enhancement. Understanding and mitigating these broader effects remains an open question for future research.

- Results suggest that the epistemological quality of responses on climate information of current LLMs is substantially lower than the presentational quality.
- We find preliminary evidence that summarizing the evaluation dimensions in the prompt can improve performance on the epistemological dimensions.
- We notice trade-offs between dimensions. Most notably, there seems to be a trade-off between epistemological and presentational quality.
- We analyze the relation of our evaluation and attribution-based evaluations of LLMs (Rashkin et al., 2022) and find that they emerge as mostly orthogonal and complementary.

2. Evaluative Dimensions

Scholarship on science communication – originating from disciplines such as communication science, sociology, psychology, human geography, and education, among others (Trench & Bucchi, 2021; Nisbet et al., 2018; Jamieson et al., 2017) – offers conceptual arguments and empirical evidence for appropriately disseminating scientific information, e.g., on climate change, to the general public (König et al., 2023; Lewis Jr. & Wai, 2021). Building on this knowledge, we distinguish between two basic dimensions. (1) *Presentational* features of the message that address its comprehensibility (Lang, 2000). (2) *Epistemological* features aiming to capture the degree to which the conveyed information represents current scientific knowledge adequately and comprehensively, while being specific and appropriately communicating associated uncertainties (Fähnrich et al., 2023).

2.1. Presentational Adequacy

An adequate *presentation* should comply with three criteria (Jamieson et al., 2017): (1) be comprehensible, (2) aid understanding through layout and visualizations, and (3) use appropriate sources and references. Here we focus primarily on *comprehensibility*, evaluated along four criteria: style, clarity, linguistic correctness, and tone.

Style. The language should not be too informal or colloquial (Mazer & Hunt, 2008), as this can undermine the credibility of information (Scharrer et al., 2012). Answers should not be too short or too long: brief snippets of information can lead to a “feeling of knowing” (Leonhard et al., 2020), while long texts require motivation and cognitive resources that readers may not want to invest (Lang, 2000). In addition, we borrow some stylistic dimensions from the Multidimensional Quality Metrics (MQM) framework for the evaluation of translations (Lommel et al., 2013).

Clarity. Responses should be concise and clearly formulated (Maibach et al., 2023). The use of jargon and difficult technical content should be avoided (Baram-Tsabari & Lewenstein, 2013; Baram-Tsabari et al., 2020).

(Linguistic) Correctness. As in MQM, messages should adhere to linguistic conventions, i.e., the correct use of punctuation, spelling, and grammar.[2] Violations can damage perceived credibility (Berger, 2020; Mollick, 2014)

Tone. The tone of a message concerns its perceived neutrality, its persuasiveness and its positivity or negativity. Science communication, especially climate-related, can be more effective if it doesn't lean towards a certain valence, worldview, or ideological conviction (Blanton & Ikizer, 2019; Yuan & Lu, 2020; Kerr et al., 2022; Munoz-Carrier et al., 2020). Likewise, messages should not use too positively or negatively valenced language, particularly if the goal is to convey factual information (Palm et al., 2020).

2.2. Epistemological Adequacy

The epistemological adequacy of climate-related messages is of greatest importance. This entails several aspects: (1) accuracy, (2) specificity, (3) completeness, (4) the degree of (un)certainty, and (5) the presentation of methods and methodology. Here we focus on the first four.

Accuracy. Scientific information should be *accurate* (Kelesidou & Chabrol, 2021). This is crucial, considering known issues of LLMs such as *hallucination* (Schäfer, 2023; Ji et al., 2023). We identify issues that deal with *incorrect, wrong,* or *self-contradictory* information, as well messages that take scientific findings, or anecdotal evidence, out of context (Hinnant et al., 2016).

Specificity. Information that is *relevant* to the audience should not be missed, while ignoring irrelevant information. Responses should address the *spatial* and *temporal* context; as specific, local information leads to higher perceived relevance (Lee et al., 2015; Leiserowitz & Smith, 2017; Holmes et al., 2020). In the absence of a specific time frame, the answer should generally be based on up-to-date knowledge.

Completeness. Rather than only referring to a part of the question posed, answers should be formulated in a way that addresses all aspects of the question in full (Leiserowitz & Smith, 2017; Bergquist et al., 2022). At the same time, the information given should reflect the depth and breadth of relevant scientific knowledge available regarding the topic(s) addressed (Kelesidou & Chabrol, 2021).

Uncertainty. Communicating the level of agreement and confidence regarding scientific findings, and supporting evidence, can be crucial to adequately informing the audience (Howe et al., 2019; Budescu et al., 2012; Keohane et al., 2014). This is particularly important in climate communication (Maertens et al., 2020; Chinn & Hart, 2021; Goldberg et al., 2022), scientific consensus on climate change has been found to function as a "gateway belief" and motivate public action (van der Linden et al., 2015).

2.3. Aggregation of scores across dimensions

In this paper we don't address the important question of how individual dimensions should be combined in a single metric, e.g., for model selection and benchmarking. This is a complex topic which requires assigning a value to each individual dimension. We also believe that the combination of these scores will vary by application.

3. Human Evaluation Study

We test our evaluative dimensions in a human rating study. The rating task involves evaluating an answer based on the presentational (Section 2.1) and epistemological dimensions (Section 2.2). Screenshots of the template can be found in Appendix A.10. We select candidate raters with relevant educational background (see Appendix A.7). To be admitted, after finishing a brief tutorial, the raters need to pass an admission test (see Appendix A.9). A summary of the broad demographics of participants can be found in Appendix A.7. Each answer is assessed by three human raters. We don't discourage brief consultations of external sources to clarify specific points but advise against extensive research.

3.1. Question and Answer Data

3.1.1. Questions

A comprehensive evaluation would ideally cover a broad spectrum of information needs, including the basics of climate science, mitigation and adaptation, as well as context-specific issues; e.g., to address the concerns of vulnerable or under-resourced communities (Amini et al., 2023). However, no standardized tests exist to assess climate-related knowledge; in contrast to e.g. the medical domain (Singhal et al., 2023). Hence, we begin by creating a diverse set of 300 questions about topics that are either popular among search users, controversial or context-specific.

We collect questions from three different sources. For the first set, we use Google Trends, which provides data on public interest in specific search topics.[3] We collect the most popular questions, by search volume, from the U.S., for the topics 'Climate Change' and 'Global Warming' for 2020-2022. For the second set, we turn to Skeptical Science, a website that publishes authoritative information about climate science. We take the list of debated *myths*[4] and manually rephrase them as questions. Lastly, we use `GPT-4` to

[2] https://themqm.info/typology.

[3] https://trends.google.com/trends/

[4] https://skepticalscience.com/argument.php

generate synthetic questions from the English Wikipedia. We manually select a list of articles related to climate change (e.g., "Global Dimming", "Polar Amplification"), or discuss the topic in specific locations (e.g., "Climate Change in [COUNTRY]"), for a total of 139 articles. Then we split the documents in paragraphs and ask GPT-4 to generate questions that can be answered by the paragraph. We apply several filters to assure that the Wikipedia questions are not overly dependent on the context and are therefore answerable only from the given paragraph. See Appendix A.3.1 for more details and a discussion of filtering choices.

We post-process all questions to remove duplicates, questions that are not related to climate change, or taken out of context. Finally, we sample 100 questions from each set.

3.1.2. Answers

Generated answers can display a great deal of variation depending on prompt engineering, reasoning schemes, in-context learning, etc. However, a direct question is the most common way for users to get answers from LLMs. As such, a plain question provides a valuable baseline, reducing variance due to individual LLM's skills and optimization effort, and limiting confounding factors. To obtain answers we use a simple prompt consisting of the instruction: *You are an expert on climate change communication. Answer each question in a 3-4 sentence paragraph.* We include the answer length information to anchor the expected response to an objective value.

3.2. Auxiliary Data

We support raters with AI Assistance, consisting of a model-generated critique for each evaluated dimension. For epistemological dimensions the assistance is grounded in verbatim evidence from relevant passages extracted from Wikipedia articles. To produce all necessary auxiliary data we carefully design a simple, robust baseline system (Figure 1), which relies on a single LLM. For consistency, we always use GPT-4 for this purpose. Besides testing our evaluation we also run a comparison with an attribution-based evaluation (AIS) (Rashkin et al., 2022), on the same data.

Keypoints. To find supporting evidence for an answer, for AI Assistance and AIS evaluation (Section 4.6), we extract keypoints from each answer. To do so, we instruct GPT-4 to examine all the statements in the answer, and identify one to three key statements that are made in answering the question. We find this to provide better signal to retrieve evidence (see the next paragraph) than either using the whole answer or all sentences individually (Liu et al., 2023).

Evidence. For each keypoint we fetch evidence from Wikipedia. Given the question and the answer, we first ask GPT-4 to provide the URL of a Wikipedia article that supports the answer. See Table 8 for the exact prompt. We limit evidence to Wikipedia because GPT-4 is fairly consistent in generating relevant, valid Wikipedia URLs, while the quality is lower for the unrestricted web. Furthermore, Wikipedia is uniform in style and quality as it adheres to established guidelines.[5] While random web pages can vary significantly in content and presentation quality.

We break down the relevant article into its paragraphs. For each keypoint, we ask the model to score the paragraphs based on their relevance to the keypoint and the question. We pick the 3 highest scoring ones as evidence (cf. Table 18 for an example). We find that using keypoints, in combination with URL generation and evidence selection, is a simple and effective solution. In particular, we find this to work better than off-the-shelf sparse or dense retrieval (e.g., using BM25/GTR (Ni et al., 2022)) over Wikipedia passages.

AI Assistance. To assist human raters, we use GPT-4 to critique the answer along the dimensions introduced in Section 2. For each dimension, we ask the model to express its agreement or disagreement that the information is presented well according to that dimension. For epistemological dimensions, we also provide the retrieved evidence and instruct the model to quote the evidence verbatim to support its disagreement (if any).

Please refer to Table 8 for a complete list of prompts used to generate the data, and to Appendix A.5 for some statistics of the generated answers.

4. Experimental Results

Here we present the findings from the experiments using Figure 2 as a summary. Full results tables, including confidence intervals, are reported in Table 3 and Table 4. We also report pairwise LLM t-tests in Tables 5 and 6. We compute pairwise distance and Krippendorff's alpha agreement metrics for all experiments in Appendix A.11, including an analysis of rating timing Appendix A.16. Accurate rating of climate information is challenging, but we find the main conclusion proposed below to be adequately supported.

LLMs. We evaluate the following models: GPT-4 (OpenAI, 2023), ChatGPT-3.5, InstructGPT (turbo), InstructGPT (text-davinci-003), InstructGPT (text-davinci-002)[6], as well as PaLM2 (text-bison) (Anil et al., 2023) and Falcon-180B-Chat[7]. This data was collected in the months of September and October 2023.

[5] https://en.wikipedia.org/wiki/Wikipedia:Policies_and_guidelines.

[6] https://platform.openai.com/docs/models.

[7] https://falconllm.tii.ae/falcon.html.

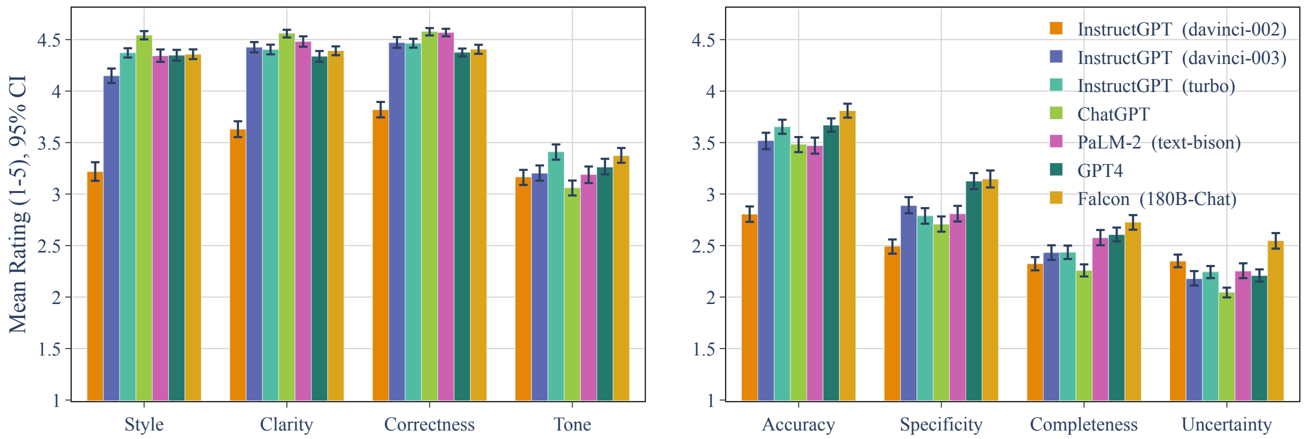

Figure 2. Bootstrapped mean rating, and 95% confidence intervals, for all presentational (left) and epistemological (right) dimensions.

4.1. Performance Results

Presentational Results. Overall, except for `InstructGPT` (text-davinci-002), LLMs produce clear, fluent, linguistically correct text. This confirms how far LLMs have come in terms of surface form quality, seemingly thanks to RLHF (Ouyang et al., 2022). We note, however, a marked performance drop for *tone*. This suggests that the evaluation of LLM's presentation should probably shift its focus on subtler aspects of language use (cf. also Section 4.4).

Epistemological Results. Compared to presentation, the epistemological evaluation reveals lower performance across all models and dimensions. Results are consistently low for the last three: *specificity*, *completeness* and *uncertainty*. We note that these dimensions may be difficult to satisfy in short 3-4 sentence answers. Being comprehensive in such a short space may be harder than being accurate.

On the other hand, LLMs don't seem to make a good use of space (see Section 4.4). Thus, space constraints alone do not seem sufficient to explain the result. Overall, on climate information, current top-of-the-line LLMs have significant headroom for improvement. For examples, please see Tables 27 to 30.

Dimension-Aware Prompts. In a follow-up experiment, using only `GPT-4`[8], we found that including a description of the evaluation criteria in the prompt can improve performance on the difficult dimensions: epistemological and *tone*. Table 1 compares `GPT-4` with either the 'basic' or 'dimension-aware' prompts (see Table 8 for the actual prompt's text). Interestingly, better performance on "knowledge" comes at the cost of worse quality in the presentational dimensions (except for *tone*), providing additional evidence for the existence of intrinsic tradeoffs between surface and epistemological quality.

Dimension	Basic prompt	Augmented prompt
Style	4.33	4.10
Clarity	4.34	4.24
Correctness	4.43	4.29
Tone	3.34	3.59
Accuracy	3.77	3.92
Specificity	3.29	3.46
Completeness	2.72	2.97
Uncertainty	2.73	2.92

Table 1. `GPT-4` with basic vs. evaluation-aware prompts.

4.2. Resolution and Range.

The results suggest that the evaluation possesses sufficient resolution to distinguish models on specific dimensions, indicate where they differ and suggest trends. For instance, `ChatGPT` is the best on all presentation dimensions, except *tone*, but ranks between position 4 and last on the epistemological scores. This indicates the possibility of complex dependencies between presentational and epistemological properties. As a matter of fact, `GPT-4` is always better than `ChatGPT` across the epistemological dimensions but worse on most presentational ones.

The difference between the best LLM and the worst in specific dimensions – e.g., `Falcon-180B-Chat` and `InstructGPT` (text-davinci-002) on the epistemologi-

[8] This experiment was carried out in November 2023, after a major release from OpenAI, on Nov 6. `GPT-4`'s performance cannot be directly compared with the previous results, because `GPT-4` is also used to produce the auxiliary data.

Question: Are we heading towards an ice age?	
Answer: No, we are not heading towards an ice age. The current scientific consensus is that human activities, particularly the emission of greenhouse gases, are causing the planet to warm at an unprecedented rate. This rapid warming is leading to a variety of climate changes, including more frequent and severe heatwaves, rising sea levels, and changes in precipitation patterns. While natural processes have triggered ice ages in the past, these are very slow processes that take thousands of years, and the current rapid warming trend is not consistent with the onset of a new ice age.	

Table 2. Example of common LLMs' argumentative style.

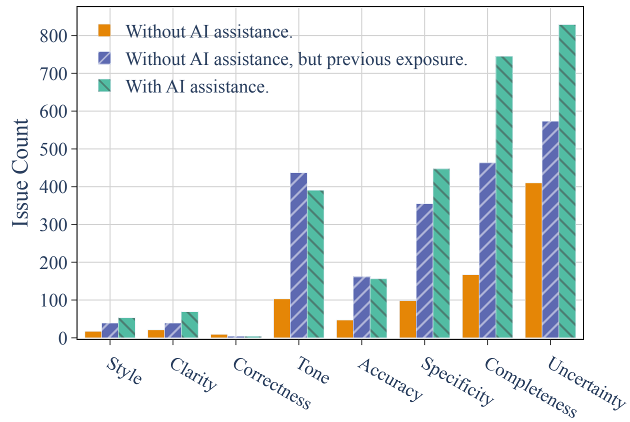

Figure 3. Number of issues detected depending on AI Assistance exposure.

cal ones, and, respectively, `ChatGPT` and `InstructGPT` (text-davinci-002) on the first three presentational ones–is large compared to the estimated standard deviation, providing evidence that the evaluation has sufficient dynamic range. Noticeably, the most competitive model–at the time of writing–on the epistemological dimensions is an open model, `Falcon-180B-Chat`. This LLM's performance may be related to its large size, but we can only speculate as this information is not generally available for all models.

4.3. Influence of Question Source.

Comparing the rating outcome by source of the question – Skeptical Science, GTrends, and synthetic questions from Wikipedia-–we find no major differences, except for slightly lower scores for Wikipedia questions. In particular, we see no evidence that `GPT-4` performs better on questions that were generated with `GPT-4` compared to the other sources. Similarly, the topic of the question does not show a strong correlation with answer quality. See Appendix A.13 for additional discussion and figures.

4.4. Pragmatic Style

LLMs often fill parts of the answer with somewhat relevant but unspecific, cautionary and sometimes preachy reminders. The example in Table 2 illustrates the point. Due to the highlighted part, the response may result in sub-optimal *cooperative conversation*, in a Gricean's sense (Levinson, 1983). For instance, one could argue that the *maxim of quantity* is being violated ('do not provide more information than required') as most of what follows the first sentence is strictly speaking unnecessary. The *maxim of manner* ('be relevant') may also be violated: comments on extreme weather and rising sea levels are only loosely related to the question. That space could be used to provide more specific information.

Furthermore, the answer relies generically on the notion of *scientific consensus*, which happens relatively frequently in our data. Besides the possibility of being superficially interpreted as an 'argument from authority', research suggests (Orchinik et al., 2023) that the 'consensus' argument can be surprisingly ineffective due to complex belief system underlying how such arguments are processed. Orchinik et al. (2023) argue that perceived scientists credibility, which in turn may depend on general worldview, affects how consensus-based messages are received and receptiveness to future messaging. This presentation style may not appeal to the different audiences of science communication and possibly lead to diminished interest and fatigue (Schäfer et al., 2018). To further complicate the picture, recent work points out that after conversing with AI on climate change, people with a skeptical stance end up dissatisfied but also more supportive of scientific consensus (Chen et al., 2024)

In these respects, LLMs answers differ from some human experts' answers to similar questions.[9] The latter tend to rely on direct and specific scientific evidence; e.g., in the case of the question above, an expert may cite land, atmospheric and ocean data for temperature trends, from multiple scientific sources.[10] Our framework captures some of these aspects in dimensions like *tone* and *specificity*, but the pragmatics aspects of Generative AI should probably be investigated more directly in the future.

4.5. Role of AI Assistance.

We expect human raters to identify more (real) issues with assistance, because it makes them aware of them. We find supporting evidence in two separate experiments.

Figure 3 reports the number of issues detected for each di-

[9]E.g., from `https://climatefeedback.org/` or `https://skepticalscience.com/`.

[10]Human experts' answers also tend to include images summarizing quantitative data.

mension on GPT-4 answers in three different settings, each with a different degree of the raters' exposure to assistance. 'Without AI Assistance' refers to a setting where a specific pool of raters is never exposed to rating with AI Assistance. 'Without AI Assistance, but previous exposure' refers to a setting where no assistance was shown, but the raters have worked on previous studies that included assistance.[11] Lastly, 'With AI Assistance' denotes the standard setting where assistance is shown anytime is available.

Results suggest that the presence of assistance is key for detecting more issues. This is consistent with the results from Saunders et al. (2022). Raters with previous exposure to assistance are in a "middle" position: They detect more issues than the assistance-unaware group, but less than the group provided with assistance for the experiment. This suggests that raters learn from repeated exposure to assistance, and show improved performance even when no assistance is present.

Further evidence of the usefulness of AI Assistance comes from our validation experiments (cf. Appendix A.14 for more details). Similar to Saunders et al. (2022), we want to determine if assistance helps surface real issues, without general access to gold truth in our data. To do this, the authors manually generated 30 different examples, each exhibiting a particular issue. We found that the majority of three raters detected 77% of issues when shown assistance, while the majority of three raters only detected 60% of the issues when not shown assistance.

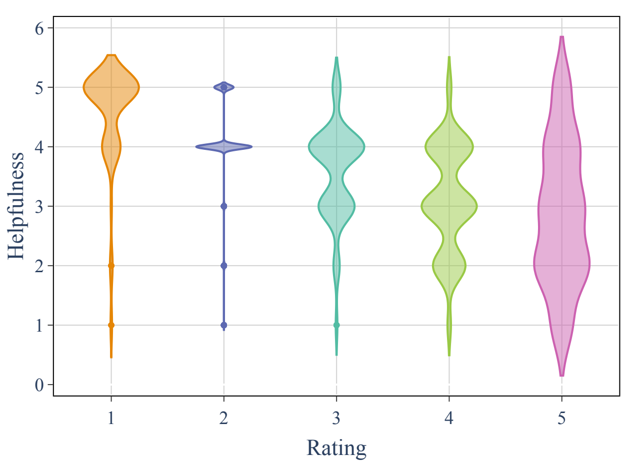

Figure 4. The relationship between rating and reported helpfulness of the AI assistance (on the same scale).

In our experiments we collected feedback from raters on the helpfulness of assistance. The data suggests that when raters do not find assistance helpful, they give higher ratings (see Figure 4). This indicates that the raters can think critically about the assistance and do not follow it blindly. These experiments provide evidence that the AI Assistance helps the raters find real issues that they would not have otherwise been reported.

4.6. Epistemological Adequacy and Attribution

Grounding LLMs responses in retrieved documents, or Retrieval Augmented Language Models (RALM) (Guu et al., 2020; Lewis et al., 2020), has been proposed to improve LLMs' response quality and alleviate factuality limitations (Menick et al., 2022). Analogously, on the evaluation side, frameworks such as Attribution to Identified Source (AIS) argue in favour of dedicated evaluations that bypass difficult direct factuality assessements (Rashkin et al., 2023; Dziri et al., 2022): an attributable answer must include an explicit quote, from an existing document. AIS signals can be also modeled automatically (Bohnet et al., 2023) enabling training via reinforcement learning (Roit et al., 2023).

While evaluating the ability of LLMs to properly ground their statements goes beyond the scope of this paper[12], we begin examining the relationship between attribution and the epistemological dimensions with an AIS experiment. We run this experiment only on GPT-4.

In our data, each answer is associated with a set of keypoints which, in turn, are used to identify Wikipedia articles that are likely to contain supporting evidence. For 87.7% of the questions, GPT-4 produces a valid Wikipedia article from which evidence passages can be extracted. We evaluate the attribution of each keypoint individually by asking the human annotators whether a keypoint is fully, partially or not supported by the evidence. 66.79% of keypoints are either fully or partially supported. We consider an answer to be fully attributed if all its keypoints are supported. An answer is not supported if all its keypoints are not supported At the answer level, 46.08% of the answers are fully or partially supported by the evidence. While providing only preliminary evidence, the data suffices for a first analysis.

Figure 5 compares the distribution of average epistemological ratings, with respect to the attribution of answers, revealing interesting trends. In both the *accuracy* and *specificity* dimensions, we observe that answers that are fully attributed have higher minimum ratings compared to answers that are only partially attributed, or not attributed at all. Interestingly, we see an opposite pattern in the *completeness* dimension: Answers that are fully attributed have lower minimum ratings on *completeness*. This result highlights a blind spot for attribution methods; AIS can only consider

[11] We do make sure that the raters have not worked on the same examples before and have never seen assistance for the specific examples they are working on.

[12] For instance, as proposed by Liu et al. (2023), this may involve evaluating generative search engines.

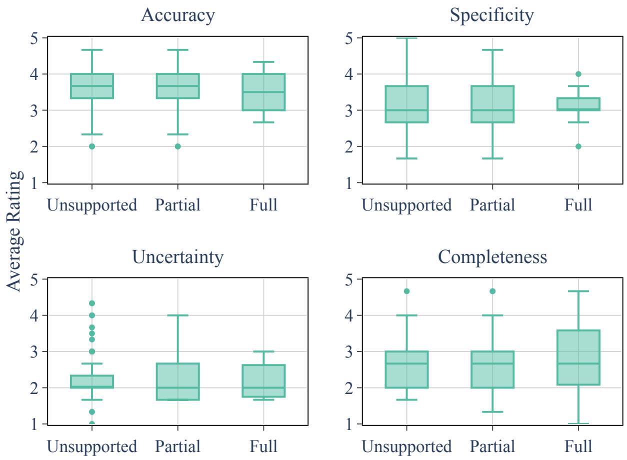

Figure 5. Comparing AIS ratings with average ratings of the 4 epistemological dimensions.

what *is* included in the answers, and not what important information is missing. In the *uncertainty* dimension, we observe that there are more answers with low uncertainty ratings among the answers that are not attributed, compared to answers that are either partially or fully attributed.

More generally, there does not seem to be any correlation between AIS and epistemological results. The Spearman's coefficient between AIS and the 3-raters mean rating value for *accuracy*, *specificity*, *uncertainty* and *completeness* are, respectively: 0.03, -0.06, 0.002, -0.02, with corresponding p-values: $0.65, 0.31, 0.97, 0.78$. We interpret this as evidence that AIS and epistemological assessments are mostly orthogonal. We provide a few examples in Table 19, in particular, of answers that are fully attributable but score low on epistemological dimensions. This suggests that, while practical and complementary, attribution, either human or model-based, is not a substitute for direct epistemological assessment.

Science and climate communication is more likely to be trusted if the source is perceived as credible, engaged and concerned about the audience's interests (Brown & Bruhn, 2011; Maibach et al., 2023; Hayhoe, 2018). An adequate presentation of climate information should include curated references. In future work we plan to extend our framework to evaluate references in a principled, systematic ways.

5. Limitations and Future Work

While our agreement analysis (Appendix A.11) suggests that the evaluation is robust at the system level, the rating dimensions inherently have a subjective component, introducing noise when evaluating at the answer-level. As we do not have access to gold ratings, calibration of raters remain an open issue, as reflected by the medium inter-rater agreement discussed in Appendix A.11. Future work should consider explicitly addressing this subjectivity in the data collection process (cf. Rottger et al. (2022)).

AI Assistance is an essential part of our evaluation, because it helps raters identify issues in the answers, particularly for the epistemological dimensions. As Tables 3 and 4 shows, raters would fail to recognize many issues without the AI Assistance ('`GPT-4` no assistance'). However, the assistance may also influence the raters beyond enhancing discovery. It may only help in the discovery of some issues but not others. There may also be errors caused by models falsely pointing out issues and wrongly convincing the raters. The issues identified will likely vary by model. There is definitely a need to better understand these issues and to identify mitigation strategies. This links this research to the broader AI alignment field and will be one of the main focuses of our future work. A related topic is the role of LLMs as raters. Preliminary experiments are promising (Appendix A.15). We found that, as with humans, LLMs benefit from AI Assistance and that humans and LLM raters tend to agree on major points.

Ideally, an answer would be tailored towards the audience, and take into account their specific attributes (Hendriks et al., 2016; Klinger & Metag, 2021). Unless specifically prompted, LLMs do not do this and the evaluation of such setting would introduce additional challenges. Another important area for future work concerns multimodal responses. Research provides abundant evidence on the importance of supplementing textual information with visual aids. (Fleming et al., 2018; Brown & Bruhn, 2011). Visual complements can be especially useful for understanding quantitative data (Fagerlin & Peters, 2011) and in the case of limited literacy (Wolf et al., 2010). The abstract nature of climate change, and its distant implications, makes visualization particularly challenging (Schäfer, 2020).

6. Related Work

Evaluating LLMs. While LLMs can generate fluent text, responses are not always adequately grounded, attributable to reliable sources, and complete. For instance, Liu et al. (2023) assess four generative search engines and report that, although responses are perceived as high quality, only half are fully supported. Their findings reveal an inverse correlation between fluency/utility and evidential support. Xu et al. (2023) advocate for expert-level human evaluations in question answering, cautioning against over-reliance on single metrics instead of comprehensive assessments.

Another domain that needs expert-level evaluation is the medical domain. Singhal et al. (2023) propose Med-PaLM, an LLM for medical information, and introduces a clinical evaluation framework which covers criteria like alignment with scientific consensus, potential harm, and comprehension. Evaluating LLMs on climate information is another domain that can benefit from expert-level evaluation. However, prior work mainly focused on text classification tasks (Diggelmann et al., 2020; Varini et al., 2020; Coan et al., 2021; Paschoal et al., 2021; Webersinke et al., 2022; Bingler et al., 2022; Spokoyny et al., 2023; Lacombe et al., 2023). This study aims to fill this gap by providing a comprehensive evaluation framework for generative climate information.

Scalable Oversight. This area, introduced by Amodei et al. (2016), studies the question of how to scale human oversight, especially in the setting where evaluating (or supervising) models becomes increasingly difficult. Contributions have initially focused on theoretical proposals for how AI can help humans supervise models that exceed their abilities (Irving et al., 2018; Leike et al., 2018; Christiano et al., 2018). Following Irving et al. (2018), one can see our AI Assistance as a single-turn debate, where the human annotator is shown the answer proposed by the model and a single response to that answer.[13]

Two recent studies provide interesting proofs of concepts for AI Assistance: Bowman et al. (2022) study *sandwiching*, an approach where non-experts align a model with the help of a model while experts provide validation. They show that non-expert raters perform better on an (artificially) difficult multiple-choice task when interacting with a dialogue agent. Several studies also evaluated short debates in this setting with mixed results (Parrish et al., 2022b;a; Michael et al., 2023). Saunders et al. (2022) report that human raters of summarization tasks produce more critiques when given the opportunity to accept or edit critiques written by a model. Our work contributes a study of a *scalable oversight* protocol to improve rating quality in a realistic setting.

AI Ratings. Recent studies explore the feasibility of evaluations performed by AI. Kocmi & Federmann (2023) indicate that LLMs can perform state-of-the-art quality assessment of translations, even without references. Their work has been extended to automatic MQM annotation by Fernandes et al. (2023). Gilardi et al. (2023) reports that ChatGPT has a higher agreement with expert-level raters than with less qualified ones. Chiang & Lee (2023) argue that humans and LLMs ratings are correlated but point out LLM's factuality and bias limitations. Instead of replacing human raters entirely, in our work we demonstrate the effectiveness of using AI Assistance to aid educated raters.

[13]In the setting of Irving et al. (2018), this corresponds to the second level of the polynomial hierarchy Σ_2^P.

7. Conclusion

We introduce an evaluation framework informed by science communication research and assess LLMs on a first set of climate information needs. The task is difficult for human raters. To support them, an important part of our framework relies on a novel and practical protocol for scalable oversight that leverages AI Assistance. It is important to realize that these are the first results of this kind and more research is needed. In particular, while there is evidence that AI Assistance is valuable, we need to develop a framework to understand and mitigate undesired influence on the raters. Overall, our results suggest that, while presentationally adequate, current LLMs have much room for improvement regarding the epistemological qualities of their outputs. More research is needed to understand and improve these aspects of LLMs.

Impact Statement

In this work we present an evaluation framework to assess the quality of answers to climate-related questions. Our evaluation is based on science-communication principles and aims to evaluate responses to genuine information needs of the public. Progress in correctly answering such questions can have a large impact for the dissemination of scientific results and can lead to positive effects on climate literacy, also reducing the public's susceptibility to misinformation.

As with any evaluation there are however limits to its validity. Specifically, the evaluation of systems to be deployed in critical contexts requires additional grounding and expert verification. This is especially the case when system responses inform actions. Moreover, the evaluation is limited to the evaluated context, and we make no claims that models can be trusted and deployed outside of that context.

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A. Appendix

A.1. Main Results

Tables 3 and 4 report the full results for all evaluated models.

System	style	clarity	correctness	tone
ChatGPT	4.54 [4.50, 4.58]	4.56 [4.52, 4.60]	4.58 [4.54, 4.61]	3.06 [2.99, 3.13]
InstructGPT (davinci-003)	4.15 [4.08, 4.22]	4.43 [4.38, 4.47]	4.47 [4.42, 4.52]	3.20 [3.12, 3.28]
InstructGPT (davinci-002)	3.22 [3.13, 3.31]	3.63 [3.55, 3.70]	3.82 [3.74, 3.90]	3.17 [3.09, 3.24]
InstructGPT (turbo)	4.37 [4.32, 4.42]	4.40 [4.36, 4.45]	4.46 [4.42, 4.51]	3.41 [3.33, 3.48]
PaLM-2 (text-bison)	4.34 [4.28, 4.40]	4.48 [4.43, 4.53]	4.57 [4.53, 4.61]	3.19 [3.11, 3.27]
GPT4	4.35 [4.30, 4.40]	4.34 [4.28, 4.39]	4.38 [4.34, 4.41]	3.26 [3.19, 3.34]
Falcon (180B-Chat)	4.36 [4.31, 4.41]	4.39 [4.35, 4.44]	4.41 [4.36, 4.45]	3.37 [3.30, 3.45]
GPT4, no assistance, prev. exposure	4.59 [4.54, 4.63]	4.63 [4.59, 4.68]	4.66 [4.63, 4.70]	3.24 [3.16, 3.32]
GPT4, no assistance	4.45 [4.41, 4.50]	4.57 [4.53, 4.61]	4.74 [4.70, 4.77]	4.35 [4.29, 4.42]

Table 3. Results along the presentational dimensions, with 95% confidence intervals.

System	accuracy	specificity	completeness	uncertainty
ChatGPT	3.48 [3.41, 3.55]	2.71 [2.63, 2.78]	2.26 [2.20, 2.31]	2.05 [2.00, 2.09]
InstructGPT (davinci-003)	3.52 [3.44, 3.60]	2.89 [2.81, 2.97]	2.43 [2.36, 2.50]	2.18 [2.11, 2.25]
InstructGPT (davinci-002)	2.81 [2.73, 2.88]	2.49 [2.42, 2.56]	2.32 [2.26, 2.39]	2.35 [2.29, 2.41]
InstructGPT (turbo)	3.65 [3.58, 3.73]	2.79 [2.71, 2.86]	2.43 [2.37, 2.50]	2.24 [2.19, 2.30]
PaLM-2 (text-bison)	3.47 [3.39, 3.55]	2.81 [2.73, 2.89]	2.57 [2.50, 2.65]	2.25 [2.18, 2.32]
GPT4	3.67 [3.61, 3.73]	3.13 [3.05, 3.21]	2.61 [2.53, 2.68]	2.21 [2.15, 2.27]
Falcon (180B-Chat)	3.81 [3.74, 3.87]	3.15 [3.07, 3.23]	2.73 [2.65, 2.80]	2.55 [2.47, 2.62]
GPT4, no assistance, prev. exposure	3.86 [3.79, 3.93]	3.43 [3.35, 3.52]	3.30 [3.21, 3.39]	2.78 [2.69, 2.87]
GPT4, no assistance	4.49 [4.44, 4.55]	4.41 [4.35, 4.48]	4.32 [4.25, 4.39]	3.38 [3.29, 3.46]

Table 4. Results along the epistemological dimensions, with 95% confidence intervals.

A.2. Pairwise t-tests

Tables 5 and 6 report the results of LLM pairwise t-tests.

	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
style							
InstructGPT (davinci-002)		$--$	$--$	$--$	$--$	$--$	$--$
InstructGPT (davinci-003)	$++$		$--$	$--$	$--$	$--$	$--$
InstructGPT (turbo)	$++$	$++$		$--$	$\sim$	$\sim$	$\sim$
ChatGPT	$++$	$++$	$++$		$\sim$	$\sim$	$\sim$
PaLM-2 (text-bison)	$++$	$++$	$\sim$	$\sim$		$\sim$	$\sim$
GPT4	$++$	$++$	$\sim$	$\sim$	$\sim$		$\sim$
Falcon (180B-Chat)	$++$	$++$	$\sim$	$\sim$	$\sim$	$\sim$	
clarity							
InstructGPT (davinci-002)		$--$	$--$	$--$	$--$	$--$	$--$
InstructGPT (davinci-003)	$++$		$\sim$	$--$	$\sim$	$\sim$	$\sim$
InstructGPT (turbo)	$++$	$\sim$		$--$	$-$	$\sim$	$\sim$
ChatGPT	$++$	$++$	$++$		$\sim$	$\sim$	$\sim$
PaLM-2 (text-bison)	$++$	$\sim$	$+$	$\sim$		$\sim$	$\sim$
GPT4	$++$	$\sim$	$\sim$	$\sim$	$\sim$		$\sim$
Falcon (180B-Chat)	$++$	$\sim$	$\sim$	$\sim$	$\sim$	$\sim$	
correctness							
InstructGPT (davinci-002)		$--$	$--$	$--$	$--$	$--$	$--$
InstructGPT (davinci-003)	$++$		$\sim$	$--$	$--$	$\sim$	$\sim$
InstructGPT (turbo)	$++$	$\sim$		$--$	$--$	$\sim$	$\sim$
ChatGPT	$++$	$++$	$++$		$\sim$	$\sim$	$\sim$
PaLM-2 (text-bison)	$++$	$++$	$++$	$\sim$		$\sim$	$\sim$
GPT4	$++$	$\sim$	$\sim$	$\sim$	$\sim$		$\sim$
Falcon (180B-Chat)	$++$	$\sim$	$\sim$	$\sim$	$\sim$	$\sim$	
tone							
InstructGPT (davinci-002)		$\sim$	$--$	$\sim$	$\sim$	$-$	$--$
InstructGPT (davinci-003)	$\sim$		$--$	$\sim$	$\sim$	$\sim$	$--$
InstructGPT (turbo)	$++$	$++$		$\sim$	$\sim$	$\sim$	$\sim$
ChatGPT	$\sim$	$\sim$	$\sim$		$-$	$--$	$--$
PaLM-2 (text-bison)	$\sim$	$\sim$	$\sim$	$+$		$\sim$	$--$
GPT4	$+$	$\sim$	$\sim$	$++$	$\sim$		$-$
Falcon (180B-Chat)	$++$	$++$	$\sim$	$++$	$++$	$+$	

Table 5. Presentational dimensions - Pairwise t-test results. $--$ and $++$ indicate high significance ($p < 0.01$) that the model in the row scores lower/higher than the model in the colum. Single $-/+$ indicate $p < 0.05$ and $\sim$ indicates no significant difference between the models.

		InstructGPT		ChatGPT	PaLM-2	GPT4	Falcon
davinci-002	davinci-003	turbo		text-bison		180B-Chat	
accuracy							
InstructGPT (davinci-002)		−−	−−	−−	−−	−−	−−
InstructGPT (davinci-003)	++		−−	∼	∼	−−	−−
InstructGPT (turbo)	++	++		∼	∼	∼	−−
ChatGPT	++	∼	∼		∼	−−	−−
PaLM-2 (text-bison)	++	∼	∼	∼		−−	−−
GPT4	++	++	∼	++	++		−−
Falcon (180B-Chat)	++	++	++	++	++	++	
specificity							
InstructGPT (davinci-002)		−−	−−	−−	−−	−−	−−
InstructGPT (davinci-003)	++		∼	∼	∼	−−	−−
InstructGPT (turbo)	++	∼		∼	∼	−−	−−
ChatGPT	++	∼	∼		−	−−	−−
PaLM-2 (text-bison)	++	∼	∼	+		−−	−−
GPT4	++	++	++	++	++		∼
Falcon (180B-Chat)	++	++	++	++	++	∼	
completeness							
InstructGPT (davinci-002)		−	−−	∼	−−	−−	−−
InstructGPT (davinci-003)	+		∼	∼	−−	−−	−−
InstructGPT (turbo)	++	∼		∼	−−	−−	−−
ChatGPT	∼	∼	∼		−−	−−	−−
PaLM-2 (text-bison)	++	++	++	++		∼	−−
GPT4	++	++	++	++	∼		−
Falcon (180B-Chat)	++	++	++	++	++	+	
uncertainty							
InstructGPT (davinci-002)		∼	∼	∼	∼	∼	−−
InstructGPT (davinci-003)	∼		∼	∼	∼	∼	−−
InstructGPT (turbo)	∼	∼		∼	∼	∼	−−
ChatGPT	∼	∼	∼		−−	−−	−−
PaLM-2 (text-bison)	∼	∼	∼	++		∼	−−
GPT4	∼	∼	∼	++	∼		−−
Falcon (180B-Chat)	++	++	++	++	++	++	

Table 6. Epistemological dimensions. Pairwise t-test results. $--$ and $++$ indicate high significance ($p < 0.01$) that the model in the row scores lower/higher than the model in the colum. Single $-/+$ indicate $p < 0.05$ and $\sim$ indicates no significant difference between the models.

Issue	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
style							
inconsistent	4.88	1.00	0.33	0.00	1.11	0.22	0.45
repetitive	20.15	3.11	0.11	0.56	1.45	1.11	0.33
too informal	4.11	1.11	0.22	0.11	1.78	1.44	0.89
too long	1.03	1.67	0.33	0.89	2.12	2.11	0.89
too short	10.14	8.56	0.22	0.22	2.56	0.33	1.11
other	2.95	1.00	0.22	0.00	0.78	0.67	0.45
clarity							
hard math	1.67	0.44	1.67	0.33	0.67	1.56	0.00
sentences too long	1.80	1.33	0.11	0.22	1.67	3.11	1.22
too technical	3.59	1.00	0.33	0.44	1.22	2.56	0.56
other	8.60	1.00	0.33	0.11	1.56	0.44	0.78
correctness							
incomplete sentence	3.47	2.44	0.78	0.00	0.00	0.00	0.00
incorrect grammar	6.29	0.33	0.33	0.11	0.11	0.11	0.67
incorrect punctuation	2.18	0.44	0.56	0.00	0.11	0.22	0.56
incorrect spelling	0.77	0.00	0.11	0.11	0.22	0.00	0.11
other	3.98	1.11	0.00	0.11	0.45	0.11	0.78
tone							
biased	28.50	34.44	24.78	42.38	33.85	30.33	23.72
negative	1.28	1.78	1.56	1.00	5.01	3.00	1.89
persuasive	2.57	8.00	4.80	7.68	10.69	8.00	4.45
other	0.39	0.67	0.22	0.11	0.45	2.00	0.22
accuracy							
anecdotal	10.78	1.33	3.35	19.24	5.90	2.56	3.01
incorrect	20.92	10.78	5.58	3.23	11.69	4.44	4.57
science out of context	9.37	6.11	5.69	2.67	5.35	3.78	2.56
self contradictory	2.70	0.89	0.11	0.11	0.89	0.44	0.33
wrong use of terms	1.93	1.22	1.00	0.33	1.45	0.44	0.22
other	3.34	3.00	1.90	1.89	2.00	5.67	0.78
specificity							
irrelevant info	15.15	4.56	3.79	5.12	8.69	8.89	4.01
vague	49.42	44.78	48.88	58.40	51.67	39.11	35.86
other	1.67	3.44	1.45	0.56	2.12	1.67	1.34
completeness							
does not address main parts	29.91	22.56	11.16	9.79	15.92	8.78	9.47
does not address region	3.34	2.67	0.78	0.56	1.34	1.78	1.22
does not address time	2.05	4.11	1.90	0.67	0.67	2.78	0.67
ignores science	9.11	14.11	6.92	5.01	10.47	5.44	3.01
not enough detail	52.89	60.22	64.06	79.53	58.13	61.22	51.89
other	1.16	0.89	0.45	0.11	0.89	2.78	1.11
uncertainty							
consensus missing	19.77	14.89	21.99	9.34	12.14	9.89	9.80
contradicting evidence missing	4.11	6.33	2.57	2.00	4.23	3.56	2.90
uncertainty missing	57.25	75.00	72.88	87.65	71.94	76.78	58.02
other	0.90	1.11	0.45	0.11	0.45	1.89	0.33

Table 7. Percentage of specific issues identified by raters.

A.3. Questions

In this section we explain the pipeline used for selection, generation, post-processing and sampling climate change related questions. The question set consists of 300 questions, with 100 questions gathered from 3 sources each: i) Synthetic questions generated based on Wikipedia articles, ii) Manually rephrased questions based on Skeptical Science website, and iii) questions taken from Google Trends.

A.3.1. Synthetic Questions from Wikipedia

We started by gathering a set of Wikipedia articles related to climate change. We followed 3 strategies to select climate related articles from Wikipedia. Following the first strategy (REF.), we gather all the Wikipedia articles that are referenced in the main "Climate Change" article.[14] In the second strategy (CAT.), we select all the articles that are directly listed in the climate change category. Finally, to cover regional articles (REG.), we manually curate a list of articles with titles *"Climate Change in [country/region]"*. From a pool of articles gathered following these 3 strategies, we selected paragraphs within an article if the paragraph consists of more than 500 characters. In total, we obtained 1969 paragraphs from Wikipedia. The following table reports a break-down of number of paragraphs based on the selection strategy:

Strategy	# Articles	# Paragraphs
REF.	35	858
CAT.	46	434
REG.	48	677
Total	129	1969

We then input each selected paragraph in `GPT-4`. We ask the model to generate as many questions as possible that can be answered using the paragraph. The model is instructed to only generate questions that are salient and related to climate change. This process resulted in 15265 questions. We post process the questions and remove undesirable ones with 4 filters that we explain next.

Climate Change Filter. We remove all questions that are not climate change related. We use the climate-bert (Webersinke et al., 2022) classifier and label each question with two labels: climate related and not climate related. We remove 2647 questions that are not classified as climate-related questions.

Duplicate Filter. We remove questions that are a duplicate of another question. To this end, we embed all questions using a universal sentence encoder.[15] We consider two questions as duplicates if the cosine similarity between their embeddings is greater than 0.85. Therefore, we remove 1188 questions that are duplicates of other questions.

Context Dependent Filter. We filter out questions that are taken out of context. The reason that this filter is necessary is that we generate questions from paragraphs, therefore, some questions are nonsensical when they are not accompanied by the corresponding Wikipedia paragraph. An example of such a question is: *"What are the two classes of climate engineering discussed in the study?"*; without knowing which study is referred to, this question cannot be answered. To develop this filter, we build a dedicated classifier using in-context probing (Amini & Ciaramita, 2023). Specifically, we manually annotate 100 questions with two labels: context dependent, and not context dependent. Next, we contextualize the question with the instruction *"Write Yes if the query is taken out of context, write No otherwise."* and extract the last layer's representations of a `flan-xxl` encoder (Chung et al., 2022). Finally, we train a logistic regression probing classifier on the representations to detect context dependent questions. We find the context dependency filter to be 97% accurate on 100 manually annotated validation questions. Using this classifier, we detect 552 context dependent questions.

Specificity Filter. We remove questions that are asking about a very specific and narrow topic. In our study, we aim to evaluate large language models on a set of challenging and multifaceted questions that target information needs of users related to climate change. Therefore, questions that ask for a specific detail are not the target of this study and are typically easy to answer. An example of such question is: "What was the reason for shutting down reactor number one of

[14] `https://en.wikipedia.org/wiki/Climate_change`

[15] We use `universal-sentence-encoder-qa/3` model.

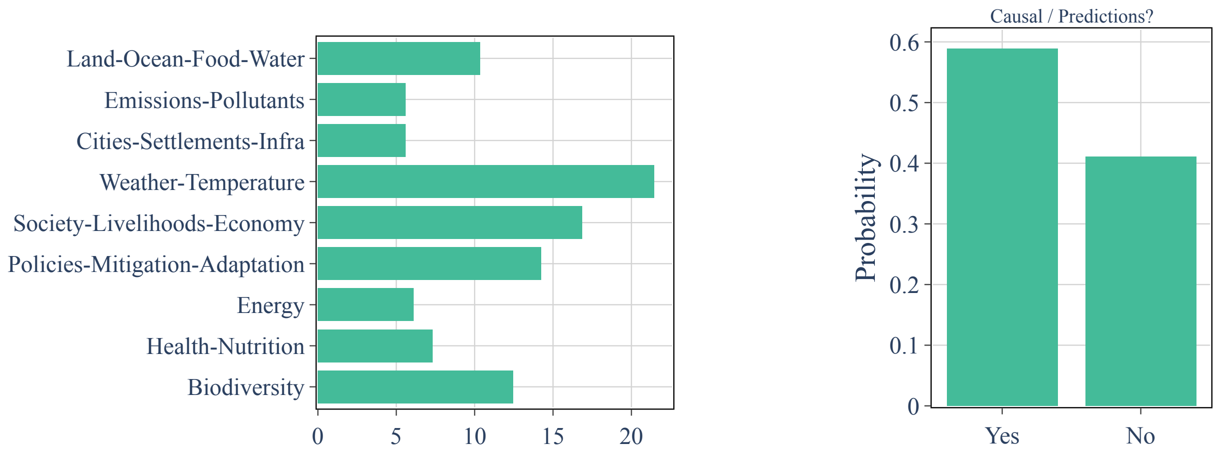


Figure 6. Left: Distribution of the topic of the synthetic questions. The x axis shows the percentage of questions in each topic. The most frequent topic is "Weather-Temperature" topic. Right: Distribution of the causal feature of synthetic questions. There are more questions that are asking causal questions, or questions about predicting the future compare to the rest of the questions.

the Fessenheim Nuclear Power Plant on 4 August 2018?" To remove such specific questions, we again build in-context probing classifier on top of `flan-xxl` representations. We contextualize each question with the instruction: *"Write Yes if the following query is asking about a specific subject, write No otherwise"*. and train the probe on top of extracted contextualized representations from the last layer of `flan-xxl`. We find the specificity filter to be 84% accurate on a sample of 100 annotated validation questions. We detect and remove 5472 specific questions.

After applying all 4 filters, the final post-processed question set consists of 5404 questions. The question set that is rated in our evaluation framework consists of 100 questions from each source. This means that we need to sample 100 diverse questions from this pool of ≈ 5k questions. To make sure that we cover different topics and type of questions, we first label each question with the topic and properties of the question, and then sample a 100 validation questions, where different topics and properties are equally presented. Next, we explain the classifiers that are developed for labeling the questions.

Topic Classifier. We use the same in-context probing approach as above and train a logistic regression classifier on top of `flan-xxl` encoder to classify questions based on the topics. Inspired by IPCC chapters, we consider the following 9 topics: *"Energy", "Emissions-Pollutants", "Policies-Mitigation-Adaptation", "Weather-Temperature", "Land-Ocean-Food-Water", "Society-Livelihoods-Economy", "Health-Nutrition", "Biodiversity", "Cities-Settlements-Infra"*. We find this classifier to be 75% accurate on a sample of 100 annotated validation questions. The distribution of predicted questions' topics is depicted in Figure 6.

Causal Prediction Classifier. An important and challenging type of questions that one can ask about climate change is about causes or effects of climate change, or predictions about the future. To detect this type of questions, we classify questions into two classes: causal-prediction class and others. The instruction that is used for contextualizing the questions is: *"Write Yes if the following query is asking about causes or effects of something, or is asking about predictions about the future. write No otherwise"*. We find this classifier to be 93% accurate on a sample of 100 annotated validation questions. The distribution of predictions is shown in Figure 6

For synthetic Wikipedia questions, we sample 108 questions, 6 from each of the 18 possible combinations of topic and causal-prediction features. We sample an equal number of questions from the other two sources, Skeptical Science and GTrends. We manually inspect all questions from all the 3 different sources. The final question set used in the evaluations consists of 300 questions, i.e., 100 questions from each source.

A.4. Prompts

Please refer to Table 8 for an extensive list of prompts used to generate the data used throughout the paper.

[16] We found that we have used *"an statement"* instead of *"a statement"* in our experiments. We did not rerun the experiments as we believe that LLMs are quite robust to minor typos and results should not be significantly affected by it. Also, doing otherwise would be wasteful.

Function	Prompt
Answer Generation	You are an expert on climate change communication. Answer each question in a 3-4 sentence paragraph.
Obtain URL	Please provide a Wikipedia article that supports your answer. Just state the url, do not include additional text. If there is no Wikipedia url supporting the answer just say "No URL".
Extract Keypoints	Now go through all the statements made in the answer. Mention 1 to 3 key statements that are made to answer the question. If you can not provide key statement/statements, only write No Keypoints. It is very important to copy the statements verbatim from the answer.
Rate Passages	You are given a statement[16] and a passage from Wikipedia. Rate how useful the passage is for evaluating the statement on a scale from 0 (completely irrelevant) to 100 (supports or contradicts the statement). Rate the passage high only if it supports or contradicts the statement. Just state the numbers in one line, nothing else. Statement: [keypoint] Passage: [par]
Presentational AI Assistance	Given the following question and answer, express your disagreement with the statement in a concise sentence in a single line. You may be provided with relevant paragraphs from Wikipedia, if so, you must use those verbatim to support your critique. If you fully agree with the statement, state "No Critique". Question: [question] Answer: [answer] Statement: [statement]
Style Statement	The information is presented well for a general audience. In particular, the answer is not too long or too short, there is no repetition in the text, and the answer is not too informal or too technical.
Clarity Statement	The answer is clear and easy to understand. For example, if there are numbers and formulae in the answer, they are easy to understand. Furthermore, sentences are not too long or too short.
Correctness Statement	The language in the answer does not contain mistakes. In particular, there are no grammatical, spelling, or punctuation errors.
Tone Statement	The tone of the answer is neutral and unbiased. In particular, the tone is not negative and the answer does not try to convince the reader of an opinion or belief.
Epistemological AI Assistance	Given the following question and answer, express your disagreement with the statement in a concise sentence in a single line. You may be provided with relevant paragraphs from Wikipedia, if so, you must use those verbatim to support your critique. If you fully agree with the statement, state "No Critique". Question: [question] Answer: [answer] Statement: [statement].
Accuracy Statement	The answer is accurate. In particular, it does not take scientific findings out of context, does not contradict itself, does not rely on anecdotal evidence, and does not misuse key terms or scientific terminology.
Specificity Statement	There is no irrelevant statement with respect to the question in the answer, and there is no vague or generic statement in the answer.
Completeness Statement	The answer addresses everything the question asks for. In particular, it does not miss any part of the question and provides enough necessary details, e.g., numbers, statistics, and details. If the question asks for a specific time range or region, the answer correctly provides that information.
Uncertainty Statement	If there is an uncertainty involved in the scientific community, the answer appropriately conveys that uncertainty. Note that it may be appropriate not to mention uncertainty at all.
Dimension-aware main prompt	You are an expert on climate change communication. Answer the question in a 3-4 sentence paragraph. The answer should be concise and tailored for a general audience. It must be clear, and easy to understand. The answer should be presented in a neutral, unbiased tone without any negative connotations or attempts to persuade. The answer should be factually accurate. The answer should be specific to the question and avoid irrelevant, generic, or vague statements. The answer should comprehensively address all aspects of the question. Where scientific uncertainty exists, the answer should appropriately reflect this, conveying the range of scientific perspectives or the limitations of current knowledge.

Table 8. Prompts used to generate answers, AI Assistance and evidence.

A.5. Answer Statistics

We report the average number of sentences and the average number of words per sentence for all models evaluated in Table 9. Although in the prompts used for answer generation we explicitly instruct the model to only use 3 to 4 sentences to answer the question, we observe that most models generate between 4 to 5 sentences. Furthermore, `InstructGPT` (turbo), `GPT-4`, and `Falcon-180B-Chat`, generate longer sentences compared to the other models.

	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
# Sentences	4.99	3.11	3.42	4.07	4.47	4.33	3.81
# Words per sentence	14.3	18.68	21.49	20.66	19.67	21.52	22.03

Table 9. Average number of sentences and words per sentence for each model. We observe 4 out of 7 models generate 4 to 5 sentences, and `Falcon-180B-Chat` generates longer sentences compared to the other models in the batch.

Age bracket	%
$[18, 25)$	43.75
$[25, 35)$	34.38
$[35, 45)$	12.50
$[45, 55)$	6.25
$[55, 65)$	3.12

(a) Distribution of age of our raters.

Sex	%
Female	56.25
Male	43.75

(b) Distribution of sex of our raters.

Ethnicity	%
White	68.75
Black	12.50
Asian	12.50
Mixed	3.12
Other	3.12

(c) Distribution of simplified ethnicities of our raters.

Country of residence	%
United Kingdom	25.00
South Africa	12.50
Portugal	12.50
United States	9.38
Greece	6.25
New Zealand	6.25
Netherlands	6.25
Poland	6.25
Canada	3.12
Germany	3.12
Czech Republic	3.12
Hungary	3.12
Italy	3.12

(d) Distribution of countries of residence of our raters.

Table 10. Demographic information of our raters.

A.6. Rating Framework Details

A.7. Rater Demographics

We are working with a group of 32 raters. The raters are all fluent in English and all have at least an undergraduate degree in a climate-related field of study. This includes environmental disciplines (e.g. environmental science, earth science, atmospheric physics, ecology, environmental policy, climate economics), and also other disciplines (including the behavioral and social sciences) as long as their academic work (coursework, project work, or otherwise) involves work on climate or environmental studies. The remaining demographics can be seen in Table 10.

A.8. Rating Statements

For presentational and epistemological accuracy we evaluate 4 dimensions each. Given a question-answer pair the raters are asked to what degree they agree with one of the statements in Table 11.[17] The raters select agreement on a 5-point scale from *completely disagree* to *completely agree*. For the two lowest choices we ask for additional details which can be selected from a list of possible issues, including *other* which allows free-text input. See Appendix A.10 for screenshots of the rating interface.

A.9. Tutorial and Admission Test

We devise a special introduction session for new participants that contains a tutorial followed by an admission test. The purpose of the session is twofold: (1) The introduction session is designed to familiarize the raters with the interface and the task. (2) Based on the session's outcome we select raters into the rating pool.

[17] Please note that when we use the shorthand *correctness* in our results, this only refers to correctness *of the language*, i.e. presentational correctness. The corresponding epistemological dimension is *accuracy*, i.e. correctness *of the answer*.

Presentational Dimensions	**Statement and possible issues**
style	The information is presented well (for a general audience).
too informal	☐ too informal/colloquial
too long	☐ answer too long
too short	☐ answer too short
inconsistent	☐ inconsistent language/style/terminology
repetitive	☐ repetitive
other	☐ other
clarity	The answer is clear and easy to understand.
sentences too long	☐ sentences too long
too technical	☐ language too technical
hard math	☐ numbers/formulae hard to understand
other	☐ other
correctness	The language in the answer does not contain mistakes.
incomplete sentence	☐ sentence is incomplete
incorrect spelling	☐ spelling mistakes
punctuation mistakes	☐ punctuation mistakes
incorrect grammar	☐ grammatical errors
other	☐ other
tone	The tone of the answer is neutral and unbiased.
biased	☐ the answer is biased
persuasive	☐ tries to convince me of an opinion/belief
negative	☐ the tone is too negative
other	☐ other
Epistemological Dimensions	
accuracy	The answer is accurate.
incorrect	☐ incorrect
science out of context	☐ takes scientific findings out of context
self contradictory	☐ self-contradictory
wrong use of terms	☐ wrong use of key terms/scientific terminology
other	☐ other
specificity	The answer addresses only what the question asks for, without adding irrelevant information.
irrelevant info	☐ includes irrelevant parts
vague	☐ too vague/unspecific
other	☐ other
completeness	The answer addresses everything the question asks for.
does not address main parts	☐ misses important parts of the answer
does not address region	☐ does not address the region the question asks about
does not address time	☐ does not address time or time range the question asks about
not enough detail	☐ does not give enough detail (e.g. numbers, statistics, details)
ignores science	☐ ignores relevant scientific knowledge
other	☐ other
uncertainty	The answer appropriately conveys the uncertainty involved.
uncertainty missing	☐ degree of (un)certainty not given when it should be
consensus missing	☐ agreement in the scientific community not given when important
contradicting evidence missing	☐ contradicting evidence (if existing) not mentioned
other	☐ other

Table 11. (on the right) Statements as presented to the raters. We query each dimension separately in the interface (Figure 10) and ask *"To what extent do you agree with the statement below?"* We also require the raters to identify particular issues for the given list if they disagree with a statement. On the left side we list the dimensions the statements belong in and a shorthand for the issue names used in tables throughout this work.

Tutorial In the tutorial (see Figure 7) we present 4 examples of increasing difficulty in the rating interface and only ask for one dimension each. Each example exhibits a particular main issue and we expect raters to identify this issue correctly. A hint is given if the rater selects a wrong answer that does not identify the issue and they can only proceed to the next item if an acceptable answer that does identify the issue is given. Regarding other issues than the main issue, one might disagree on some of these issues and we allow several possible selections. Note that to identify the main issue, a low rating (disagree completely or disagree) must be selected. Once a valid response is selected we show positive feedback and explain why the outcome is the desired one. We don't collect any data during the tutorial part.

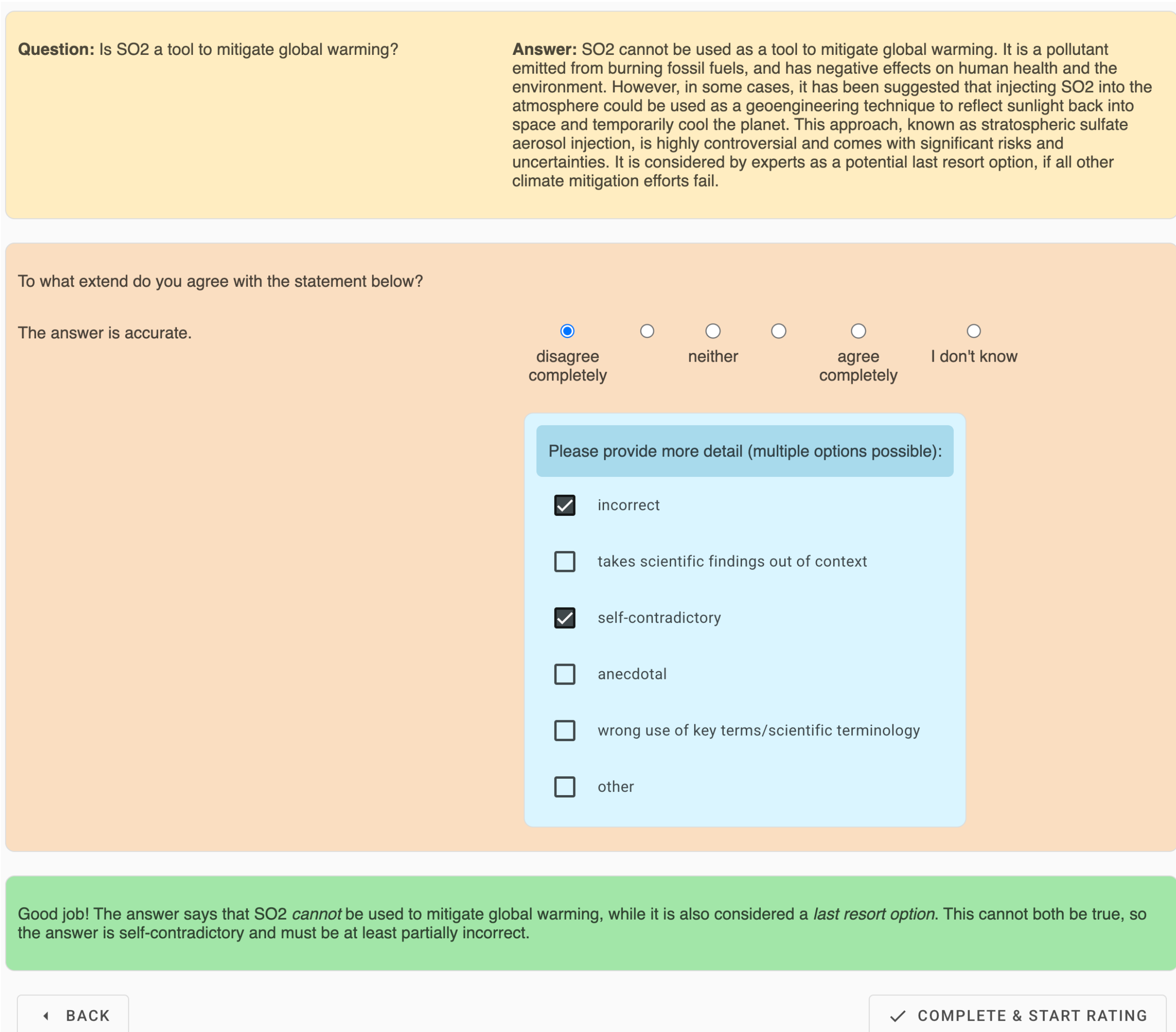


Figure 7. Screenshot of the last of 4 tutorial questions with the correct answer selected.

Admission Test To test the raters' ability and attention to detail we select three realistic examples that exhibit at least one major flaw. We use the full template and ask about all statements in Table 11. We record the responses and assign or deduct points for every detected, undetected, and over-detected issue. The point scheme was decided among the authors after carefully considering possible disagreements or subjective interpretations.

Based on the performance of an early group of raters with known performance on the task we decide on a threshold and admit raters above that score to the pool. We believe that the tutorial and admission test were effective in ensuring that raters were both familiar with the interface as well as the type of assessment we expect from them, which requires close reading of question and answer, basic knowledge of climate change, and an understanding of the tasks dimensions and issues that allows them to rate dimensions and select specific issues reliably.

A.10. Template Screenshots

We provide screenshots of our rating implementation in Figures 8 to 10.

Introduction

You are being invited to participate in a research study. We are a research team interested in using AI to provide better answers to questions about climate change, according to communication science principles. We plan to publish the data obtained with this questionnaire together with a research paper on the subject.

What will I have to do?

You are shown a question and an answer to the question. Please read both the question and the answer carefully. Your task is to help us determine how good the answer is, and whether it is supported by references. To do that, we will ask you to rate a series of statements (see below).

For some statements, AI assistance will be provided. Note that while the assistance is meant to be helpful, it may not be helpful or it may even be incorrect. We will also ask you about the helpfulness of the assistance.

The task should be self-contained. It is OK to quickly look something up, but beyond that please select “I don't know” if you can't decide based on the provided information, rather than researching additional resources like search engines or other sources.

What will I be asked?

You will be asked to assess the answer in several dimensions, rating the following statements (in bold):

Presentation

- **(Presentation) The information is presented well for a general audience.** In particular, the answer is not too long or too short, there is no repetition in the text, and the answer is not too informal or too technical.
- **(Understandability) The answer is clear and easy to understand.** Sentences are not too long / verbose or too short. If there are numbers and formulae, they are easy to understand.
- **(Correctness) The language in the answer does not contain mistakes.** In particular, there are no grammatical, spelling, or punctuation errors.
- **(Tone) The tone of the answer is neutral and unbiased.** In particular, the tone is not negative and the answer does not try to convince the reader of an opinion or belief.

Epistemology

- **(Accuracy) The answer is accurate.** Whether the answer is correct. More specifically, it does not take scientific findings out of context, does not contradict itself, does not rely on anecdotal evidence, and does not misuse key terms or scientific terminology.
- **(Specificity) The answer addresses only what the question asks for, without adding irrelevant information.** There is no irrelevant statement with respect to the question in the answer, and there is no vague or generic statement in the answer.
- **(Completeness) The answer addresses everything the question asks for.** In particular, it does not miss any part of the question and provides enough necessary details, e.g., numbers, statistics, and details. If the question asks for a specific time range or region, the answer correctly provides that information.
- **(Uncertainty) The answer appropriately conveys the uncertainty involved.** If the scientific community is uncertain about something mentioned in the answer, that uncertainty is conveyed appropriately in the answer. Note that it may be appropriate not to mention uncertainty at all.

Attribution

In the final section, you will be asked to assess whether the answer is supported by passages from Wikipedia.

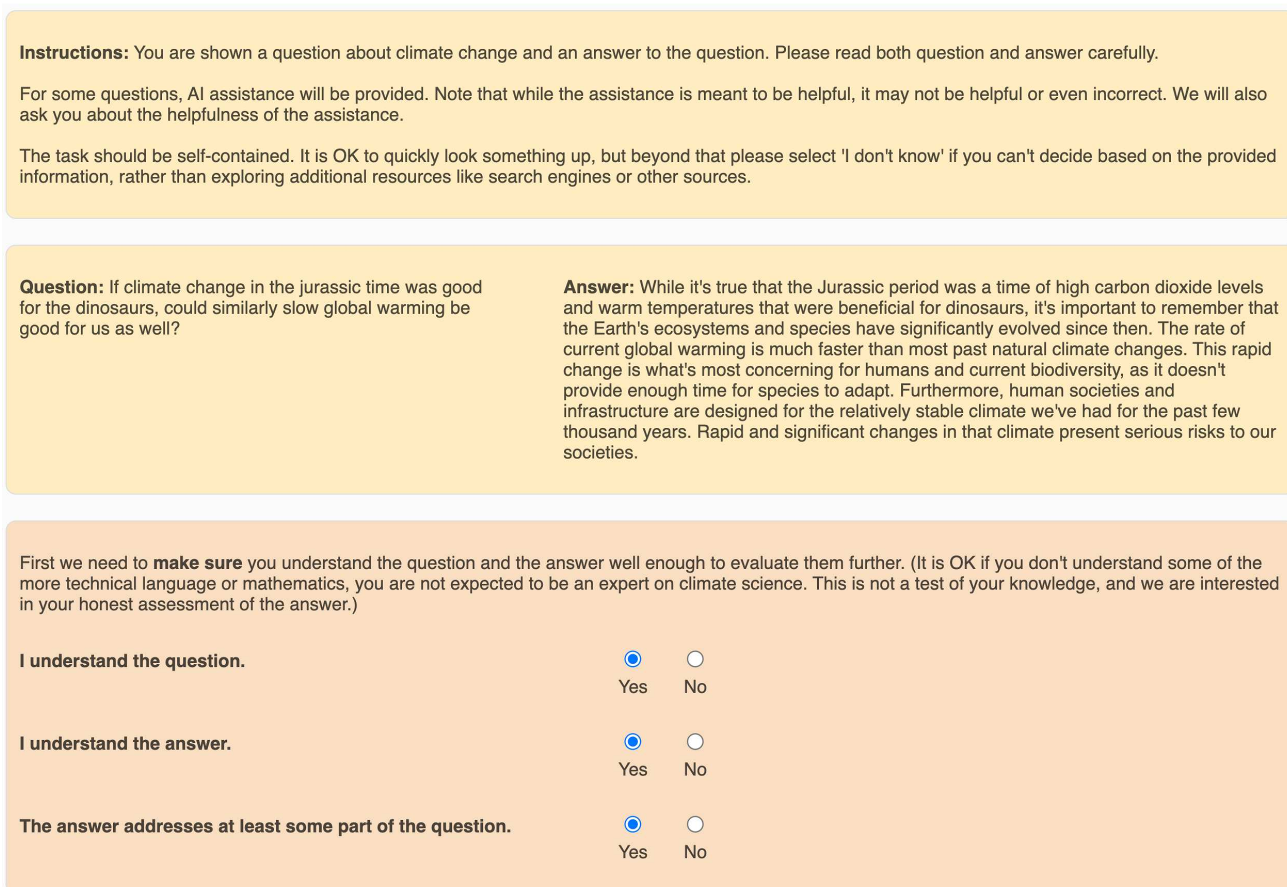
Providing detail

If you give a low rating (disagree or disagree completely), we will ask you to provide additional details. You can either select reasons from a list, or provide additional information in a text box. When offering free text, please be specific about why you gave a particular answer a low rating. This will help us add more options in the future.

Thank you for helping us provide better answers to questions about climate change! If you have any feedback or comments on how to improve this questionnaire, please send us a message on the platform.

BACK CONTINUE

Figure 8. Screenshot of the instructions to the raters, provided at the beginning of the first rating session.



Instructions: You are shown a question about climate change and an answer to the question. Please read both question and answer carefully.

For some questions, AI assistance will be provided. Note that while the assistance is meant to be helpful, it may not be helpful or even incorrect. We will also ask you about the helpfulness of the assistance.

The task should be self-contained. It is OK to quickly look something up, but beyond that please select 'I don't know' if you can't decide based on the provided information, rather than exploring additional resources like search engines or other sources.

Question: If climate change in the jurassic time was good for the dinosaurs, could similarly slow global warming be good for us as well?

Answer: While it's true that the Jurassic period was a time of high carbon dioxide levels and warm temperatures that were beneficial for dinosaurs, it's important to remember that the Earth's ecosystems and species have significantly evolved since then. The rate of current global warming is much faster than most past natural climate changes. This rapid change is what's most concerning for humans and current biodiversity, as it doesn't provide enough time for species to adapt. Furthermore, human societies and infrastructure are designed for the relatively stable climate we've had for the past few thousand years. Rapid and significant changes in that climate present serious risks to our societies.

First we need to **make sure** you understand the question and the answer well enough to evaluate them further. (It is OK if you don't understand some of the more technical language or mathematics, you are not expected to be an expert on climate science. This is not a test of your knowledge, and we are interested in your honest assessment of the answer.)

I understand the question. Yes No

I understand the answer. Yes No

The answer addresses at least some part of the question. Yes No

Figure 9. Screenshot of screening template which ensures the raters are able to judge the example. If any of the questions is answered *No* we skip the example and proceed with the next one.

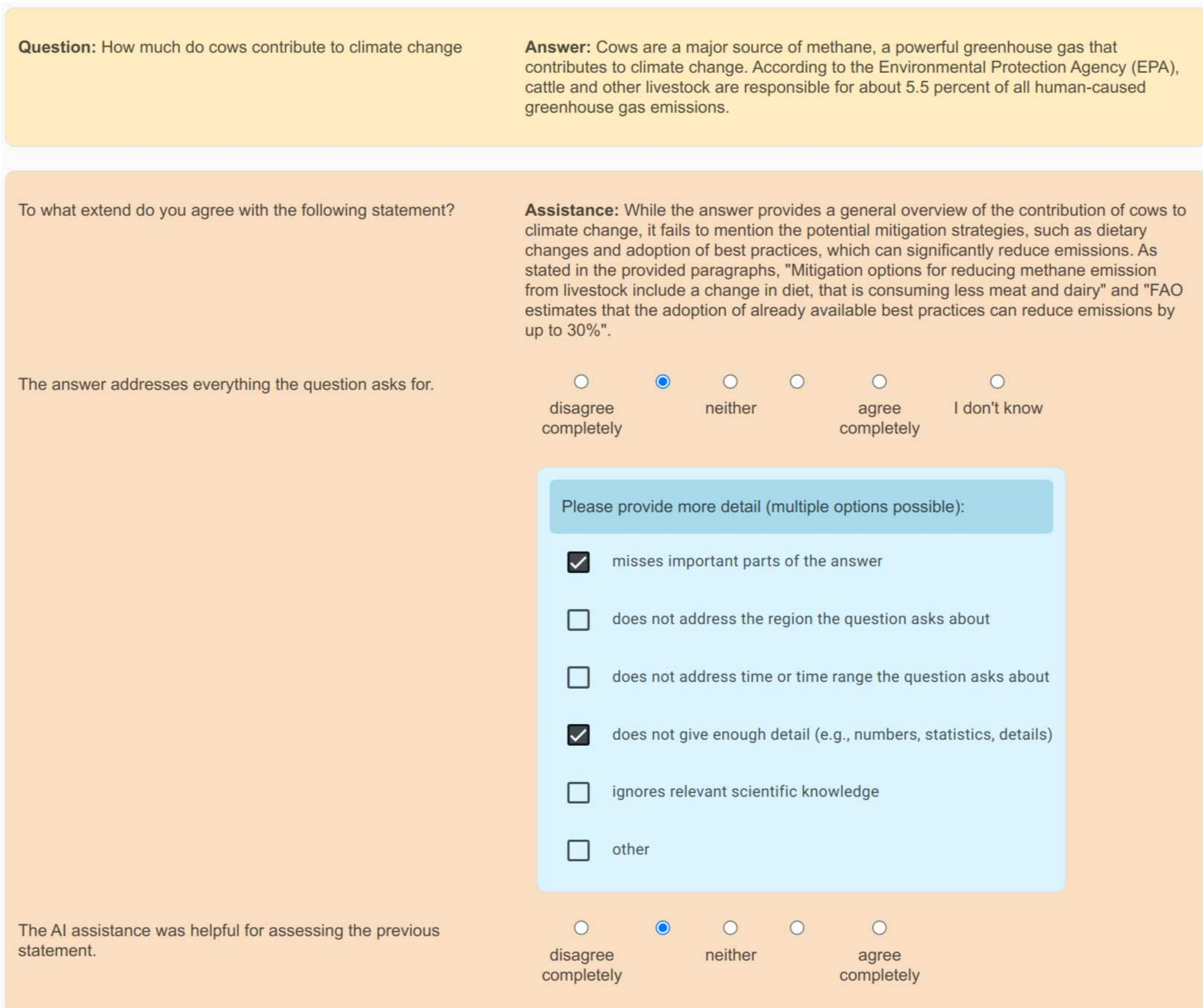


Figure 10. Screenshot of the rating interface. Here we are rating the *completeness* dimension. Since the rater selected a low rating, the interface asks for specific details. For ratings of *3 = neither* and above, the blue box is hidden. In this example we also show the AI Assistance which is not always available, which is rated as not helpful.

A.11. Inter-Rater Agreement

We first measure the agreement among raters when rating each dimension on the likert scale. In particular, we report two metrics of agreement:

Pairwise distance. We measure the average pairwise distance between the ratings. More specifically, for any 2 raters (out of 3 raters) rating the same example, we compute the absolute distance between the values they chose from the likert scale[18] and report the average for each dimension in Table 12. In general, we observe a reasonably high agreement among the raters, as the average distance is close to or below 1 in most dimensions. Notably, we observe a higher agreement in the presentational dimensions *style*, *clarity*, and *correctness*.

Issue	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
style	1.12	0.95	0.76	0.61	0.88	0.79	0.75
clarity	0.97	0.74	0.73	0.59	0.69	0.81	0.69
correctness	0.98	0.69	0.66	0.56	0.59	0.62	0.68
tone	1.16	1.26	1.21	1.30	1.36	1.22	1.23
accuracy	1.05	0.97	1.07	1.15	1.13	0.97	0.95
specificity	1.04	1.16	1.06	0.98	1.23	1.26	1.20
completeness	1.00	1.03	1.06	0.71	1.13	1.01	1.21
uncertainty	0.95	0.98	0.89	0.57	1.10	0.78	1.26

Table 12. Average pairwise distance between likert ratings for each dimension. Distances between ratings on presentational adequacy are generally lower compared to epistemological adequacy.

Krippendorff's alpha. In addition to pairwise distances, we compute Krippendorff's alpha. Krippendorff's alpha measures $1 - \frac{D_o}{D_e}$, where D_o is the observed disagreement, and D_e is the expected disagreement by chance. Values are in $[-1, 1]$ range, where 1 means complete agreement and -1 means complete systematic disagreement. Numbers in Table 13 suggest a similar trend to pairwise distance, where in most dimensions the agreement is medium, and the agreement in most presentational dimensions is higher compared to epistemological dimensions.

Issue	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
style	0.45	0.53	0.74	0.70	0.60	0.48	0.72
clarity	0.59	0.73	0.60	0.72	0.72	0.65	0.77
correctness	0.57	0.74	0.80	0.85	0.82	0.71	0.78
tone	0.48	0.36	0.41	0.31	0.25	0.36	0.41
accuracy	0.56	0.57	0.52	0.46	0.46	0.59	0.62
specificity	0.53	0.40	0.50	0.51	0.32	0.32	0.39
completeness	0.57	0.48	0.47	0.64	0.38	0.46	0.37
uncertainty	0.59	0.51	0.57	0.75	0.40	0.63	0.32

Table 13. Krippendorff's alpha of 3 likert ratings per dimension. In general we observe a medium agreement. For most LLMs the value is higher for the presentational dimensions, except tone.

Note that either measure of agreement is subject to interpretability shortcomings: Krippendorff's alpha can be misleadingly low in the case of low overall variability, i.e. when many examples are rated as 5 in a certain dimension. Likewise, average pairwise distance would appear too high.

Furthermore, we measure the agreement among raters when choosing issues. A rater might select or not select a given issue for a given answer, therefore, the value of interest is a binary variable. As above report two metrics of agreement:

Pairwise agreement. We look at the agreement among raters when selecting or not selecting a given issue. Particularly, we consider 2 raters to agree with each other on a certain issue for a given answer if they both select or both not select that issue. We then report the percentage of pairwise agreement per issue in Table 14. For the majority of issues we observe a high agreement among raters. As one might expect, issues such as "not enough detail", "vague", "uncertainty missing", and

[18] In our interface the raters agree with a statement (see Table 11) on a 5-point scale between *disagree completely* to *neither* to *agree completely* which we map to $1 \ldots 5$. See Figure 10 for a screenshot.

"biased" are more controversial and we see a lower agreement among the raters.

Krippendorff's alpha. Similarly, we compute the Krippendorff's alpha for agreement on issues and observe a similar trend in Table 15.

Looking at Table 7 we note that some issues are rarely chosen by raters and thus pairwise agreement numbers might be artificially high. For a deeper understanding regarding how well raters are able to agree on a specific issue we compute Krippendorff's alpha only for low ratings, i.e. cases where raters are required to select one or more issues. We report these numbers for a subset of dimensions with higher incidence counts in Table 16. As hinted by incidence prevalence in Table 7, we find that when raters agree on a low rating for an epistemological dimension, they also exhibit medium to high agreement on what the specific issue is. One exception is *accuracy:incorrect* which might be too generic as an issue.

Overall, agreement on specific issues is not high enough to recommend our 3-rater setup for evaluation of individual answers but for comparing and highlighting the strengths and shortcomings of models on a system level, as indicated by the fairly tight error bars in Figure 2.

Issue	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
style							
too informal	92.40	97.77	99.55	99.78	96.42	97.10	98.21
too long	98.20	98.00	99.33	98.44	96.42	95.77	98.44
too short	84.79	87.42	99.66	99.55	95.08	99.33	97.77
inconsistent	90.72	98.00	99.33	100.00	97.76	99.55	99.11
repetitive	83.63	96.88	99.78	98.88	97.76	97.77	99.33
other	94.33	98.00	99.55	100.00	98.88	98.66	99.33
clarity							
sentences too long	96.39	97.77	99.78	99.55	96.64	94.21	97.54
too technical	94.07	98.22	99.33	99.11	97.76	95.10	98.88
hard math	96.91	99.11	97.31	99.33	98.66	96.88	100.00
other	85.95	98.22	99.55	99.78	97.76	99.11	98.44
correctness							
incomplete sentence	94.33	97.11	99.55	100.00	100.00	100.00	100.00
incorrect spelling	98.45	100.00	99.78	99.78	99.55	100.00	99.78
incorrect punctuation	95.88	99.11	98.88	100.00	99.78	99.55	98.88
incorrect grammar	89.43	99.33	99.33	99.78	99.78	99.78	98.66
other	93.81	98.22	100.00	99.78	99.33	99.78	98.66
tone							
biased	60.57	59.02	67.15	48.33	57.06	59.19	64.06
persuasive	95.62	87.08	91.03	86.38	81.05	84.98	91.96
negative	97.68	96.66	97.09	98.21	90.92	95.07	96.65
other	99.23	98.66	99.55	99.78	99.33	96.08	99.55
accuracy							
incorrect	69.91	89.73	91.43	95.70	84.36	92.20	93.02
science out of context	82.70	89.35	88.76	95.22	89.17	92.46	95.56
self contradictory	95.49	98.20	99.87	99.76	98.40	98.98	99.24
anecdotal	78.05	97.18	92.37	63.80	87.17	94.63	94.67
wrong use of terms	96.22	97.69	98.26	99.52	97.46	98.98	99.49
other	93.46	93.84	96.12	96.42	95.45	89.13	98.48
specificity							
irrelevant info	75.59	90.79	92.43	89.84	84.89	84.06	93.60
vague	48.96	54.20	60.44	58.90	52.60	56.81	60.66
other	97.13	93.94	97.71	99.09	96.31	97.00	97.27
completeness							
does not address main parts	61.33	69.27	80.68	82.77	75.12	84.07	84.95
does not address region	93.36	94.78	98.41	98.87	97.30	96.59	97.92
does not address time	96.09	91.61	96.14	98.64	98.59	94.54	98.73
not enough detail	44.66	55.56	51.48	68.59	54.23	59.39	47.57
ignores science	84.24	77.55	86.93	90.82	81.57	90.22	94.91
other	97.66	98.30	99.09	99.77	98.12	94.77	97.80
uncertainty							
uncertainty missing	49.35	63.46	63.07	80.02	60.10	65.39	50.57
consensus missing	70.26	75.45	66.97	81.96	77.25	81.60	82.53
contradicting evidence missing	92.47	88.46	94.84	95.89	91.97	92.94	95.17
other	98.18	97.74	99.20	99.77	99.03	96.06	99.31

Table 14. Pairwise agreement among the 3 raters per issue. In general we observe high agreement among raters in selecting issues for all models, while some issues such as "vague", "biased", "not enough detail", and "uncertainty missing" are more disagreed upon.

Issue	InstructGPT			ChatGPT	PaLM-2	GPT4	Falcon
	davinci-002	davinci-003	turbo		text-bison		180B-Chat
style							
too informal	0.85	0.96	0.99	1.00	0.93	0.94	0.96
too long	0.96	0.96	0.99	0.97	0.93	0.92	0.97
too short	0.70	0.75	0.99	0.99	0.90	0.99	0.96
inconsistent	0.81	0.96	0.99	1.00	0.96	0.99	0.98
repetitive	0.67	0.94	1.00	0.98	0.96	0.96	0.99
other	0.89	0.96	0.99	1.00	0.98	0.97	0.99
clarity							
sentences too long	0.93	0.96	1.00	0.99	0.93	0.88	0.95
too technical	0.88	0.96	0.99	0.98	0.96	0.90	0.98
hard math	0.94	0.98	0.95	0.99	0.97	0.94	1.00
other	0.72	0.96	0.99	1.00	0.96	0.98	0.97
correctness							
incomplete sentence	0.89	0.94	0.99	1.00	1.00	1.00	1.00
incorrect spelling	0.97	1.00	1.00	1.00	0.99	1.00	1.00
incorrect punctuation	0.92	0.98	0.98	1.00	1.00	0.99	0.98
incorrect grammar	0.79	0.99	0.99	1.00	1.00	1.00	0.97
other	0.88	0.96	1.00	1.00	0.99	1.00	0.97
tone							
biased	0.21	0.18	0.34	−0.03	0.14	0.18	0.28
persuasive	0.91	0.74	0.82	0.73	0.62	0.70	0.84
negative	0.95	0.93	0.94	0.96	0.82	0.90	0.93
other	0.98	0.97	0.99	1.00	0.99	0.92	0.99
accuracy							
incorrect	0.40	0.79	0.82	0.91	0.67	0.85	0.85
science out of context	0.64	0.78	0.77	0.90	0.78	0.84	0.90
self contradictory	0.91	0.97	1.00	1.00	0.97	0.98	0.99
anecdotal	0.57	0.94	0.85	0.28	0.75	0.89	0.89
wrong use of terms	0.93	0.95	0.97	0.99	0.94	0.98	0.99
other	0.86	0.88	0.92	0.93	0.91	0.78	0.97
specificity							
irrelevant info	0.51	0.81	0.85	0.80	0.70	0.67	0.87
vague	−0.02	0.08	0.21	0.18	0.05	0.14	0.21
other	0.94	0.88	0.95	0.98	0.93	0.94	0.94
completeness							
does not address main parts	0.23	0.38	0.61	0.65	0.51	0.68	0.70
does not address region	0.87	0.90	0.97	0.98	0.95	0.93	0.95
does not address time	0.92	0.83	0.92	0.97	0.97	0.89	0.97
not enough detail	−0.11	0.11	0.03	0.38	0.09	0.19	−0.05
ignores science	0.68	0.55	0.73	0.82	0.63	0.80	0.90
other	0.95	0.96	0.98	1.00	0.96	0.90	0.95
uncertainty							
uncertainty missing	−0.01	0.27	0.26	0.60	0.20	0.31	0.01
consensus missing	0.41	0.51	0.33	0.64	0.53	0.64	0.65
contradicting evidence missing	0.85	0.77	0.90	0.92	0.84	0.86	0.91
other	0.96	0.96	0.98	1.00	0.98	0.92	0.99

Table 15. Krippendorff's alpha for agreement on issue selection. The results are consistent with patterns observed in pairwise agreement.

Issue	InstructGPT davinci-002	InstructGPT davinci-003	InstructGPT turbo	ChatGPT	PaLM-2 text-bison	GPT4	Falcon 180B-Chat
tone							
biased	0.84	0.60	0.55	0.58	0.34	0.35	0.43
accuracy							
incorrect	0.01	0.35	0.10	0.45	0.21	0.44	0.32
specificity							
vague	0.37	0.57	0.83	0.76	0.66	0.65	0.65
completeness							
does not address main parts	0.16	0.31	0.49	0.59	0.42	0.64	0.51
not enough detail	0.30	0.62	0.77	0.87	0.63	0.72	0.71
uncertainty							
uncertainty missing	0.55	0.81	0.77	0.91	0.83	0.80	0.72
consensus missing	0.26	0.42	0.25	0.61	0.45	0.56	0.54

Table 16. Krippendorff's alpha for agreement on issue selection, but computed only for low ratings.

	Per Example		Per Keypoint	
	Percentage %	Count	Percentage %	Count
Fully Supports	6.95	16	12	124
Partially Supports	39.13	90	54.79	566
No Support	53.91	124	32.81	339
Contradicts	0	0	0.38	4
Total	100	230	100	1033

Table 17. AIS results for `GPT-4` generations. We report the results both at example level, where an example can consist of multiple keypoints, and at keypoint level. We observe that the majority of keypoints are only partially supported, and only around 7% of examples are fully supported.

A.12. AIS Evaluation

In our AIS evaluation we ask human raters to assess whether each keypoint is, fully, partially, or not supported by its corresponding top 3 retrieved passages. At the keypoint level, as shown in Figure 5, the majority of keypoints are partially supported, while only 12% of keypoints are fully supported by their corresponding evidence. We further ask the raters whether the top 3 passages jointly provide support for the keypoint. We then aggregate this result in the following way. We consider an answer to be fully attributed if all its keypoints are supported. An answer is not supported if all its keypoints are not supported. Otherwise, the answer is partially supported. An example is given in Table 18. We observe (Figure 5) that only 6.95% of answers are fully supported.

Question	How could pests and diseases spread more easily under warmer conditions caused by climate change?
Answer	Climate change, particularly global warming, can facilitate the spread of pests and diseases more easily. Warmer conditions can extend the breeding seasons of pests, increase their population growth, and expand their geographical range. For instance, mosquitoes, which are vectors for diseases like malaria and dengue, thrive in warmer climates and can reproduce and mature more quickly under such conditions. Additionally, warmer temperatures can also accelerate the lifecycle of pathogens, making diseases more virulent and their transmission more efficient.
1st Keypoint	Warmer conditions can extend the breeding seasons of pests, increase their population growth, and expand their geographical range.
Paragraph 1.	Infectious diseases that are sensitive to climate can be grouped into: vector-borne diseases (transmitted via mosquitos, ticks etc.), water-borne diseases (transmitted via viruses or bacteria, e.g.: E. Coli) and food-borne diseases (e.g.: Salmonella). Climate change is affecting the distribution of these diseases due to the expanding geographic range and seasonality of these diseases and their vectors.
Paragraph 2.	Mosquito-borne diseases that are sensitive to climate include malaria, elephantiasis, Rift Valley fever, yellow fever, dengue fever, Zika virus, and chikungunya. Scientists found in 2022 that rising temperatures are increasing the areas where dengue fever, malaria and other mosquito-carried diseases are able to spread. Warmer temperatures are also advancing to higher elevations, allowing mosquitoes to survive in places that were previously inhospitable to them. This risks malaria making a return to areas where it was previously eradicated.
Paragraph 3.	Ticks are changing their geographic range because of rising temperatures, and this puts new populations at risk. Ticks can spread lyme disease and tick-borne encephalitis. It is expected that climate change will increase the incidence of these diseases in the Northern Hemisphere. For example, a review of the literature found that ”In the USA, a 2°C warming could increase the number of Lyme disease cases by over 20% over the coming decades and lead to an earlier onset and longer length of the annual Lyme disease season”.
Rating	Not Supported
2nd Keypoint	Mosquitoes, which are vectors for diseases like malaria and dengue, thrive in warmer climates and can reproduce and mature more quickly under such conditions.
Paragraphs	. . .
Rating	Supported
3rd Keypoint	Warmer temperatures can also accelerate the lifecycle of pathogens, making diseases more virulent and their transmission more efficient.
Paragraphs	. . .
Rating	Supported
Overall Rating	Partially Supported

Table 18. An example of the AIS task with ratings. Overall, the answer is only partially supported, as the first keypoint is not supported by the evidence.

Question. When did the general public become aware of carbon dioxide's effects on climate?	
Answer. The general public became significantly aware of carbon dioxide's effects on climate change around the late 20th century. The Intergovernmental Panel on Climate Change (IPCC) was established in 1988, and its assessments, which highlighted the role of carbon dioxide in global warming, were widely disseminated and discussed in the media. However, it's important to note that the scientific understanding of carbon dioxide's impact on climate predates this public awareness by many decades, with initial theories and evidence emerging as early as the late 19th century.	**AI Assistance.** While the answer provides a general timeline of public awareness of carbon dioxide's effects on climate change, it fails to mention key milestones such as the warnings of the climate crisis by Glenn T. Seaborg in 1966, or John Sawyer's study in 1972, which summarized the knowledge of the science at the time and accurately predicted the rate of global warming for the period between 1972 and 2000. These events significantly contributed to the public's understanding of the issue before the establishment of the IPCC in 1988.
AIS. Fully attributable	**Average completeness rating.** 1.6
Question. How do elevated carbon dioxide levels affect the mineral density of crops and wild plants?	
Answer. Elevated carbon dioxide levels can significantly affect the mineral density of crops and wild plants. While higher CO2 levels can stimulate plant growth, they can also reduce the concentration of essential minerals in a variety of crops and wild plants. This phenomenon, known as "CO2 dilution effect", results in crops with lower nutritional value, including reduced levels of protein, iron, zinc, and other essential nutrients. Therefore, while plants may grow larger in response to increased CO2, their nutritional quality can be significantly compromised.	**AI Assistance.** The statement fails to acknowledge the uncertainty in the potential positive impacts of elevated CO2 levels, such as higher crop yields due to CO2 fertilization, and the possibility of more arable land becoming available as frozen land thaws.
AIS. Fully attributable	**Average uncertainty rating.** 1.6
Question. Can climate sensitivity be ignored because too low?	
Answer. Climate sensitivity, which refers to the temperature change associated with a doubling of the concentration of carbon dioxide in the atmosphere, cannot be ignored even if it is low. This is because even a small increase in global temperatures can have significant impacts on the Earth's climate system. For instance, it can lead to more frequent and severe weather events, such as hurricanes and droughts, and cause sea levels to rise, which can result in coastal flooding. Therefore, understanding and addressing climate sensitivity is crucial in climate change mitigation and adaptation strategies.	
AIS. Not Supported	**Average accuracy rating.** 4.7
Question. Is global warming caused by the pacific decadal oscillation?	
Answer. No, global warming is not caused by the Pacific Decadal Oscillation (PDO). The PDO is a long-term ocean temperature fluctuation in the Pacific Ocean that shifts between warm and cool phases approximately every 20 to 30 years. While these shifts can influence regional climate patterns and marine ecosystems, they do not cause global warming. Global warming is primarily caused by human activities, particularly the burning of fossil fuels like coal, oil, and gas, which increase the concentration of greenhouse gases in the atmosphere and trap heat.	
AIS. Not Supported	**Average specificity rating.** 5

Table 19. Examples highlighting the differences between attribution scores and epistemological ratings under our framework.

A.13. Breakdown of Ratings Per Question Type

We compare the presentational and epistemological adequacy of `GPT-4` answers, based on the question source, type, and causal-prediction dimension, as described in Appendix A.3.1. Generally, there isn't a significant difference between the ratings based on the topic of the question as shown in Figure 11. However, we observe that questions in the *"Policies-Mitigation-Adaptation"* category receive lower ratings in most of the epistemological dimensions, and particularly in the *tone* dimension. We further look at the difference in average ratings based on the source of the question (Wikipedia, Skeptical Science, or GTrends), and causality of the question. The source of the question does not affect the ratings significantly (please refer to Figure 12). However, we observe that Wikipedia questions tend to receive lower epistemological adequacy ratings. This could be because these questions ask for more details and very specific info compared to GTrends and Skeptical Sciences, and thus are harder to answer.

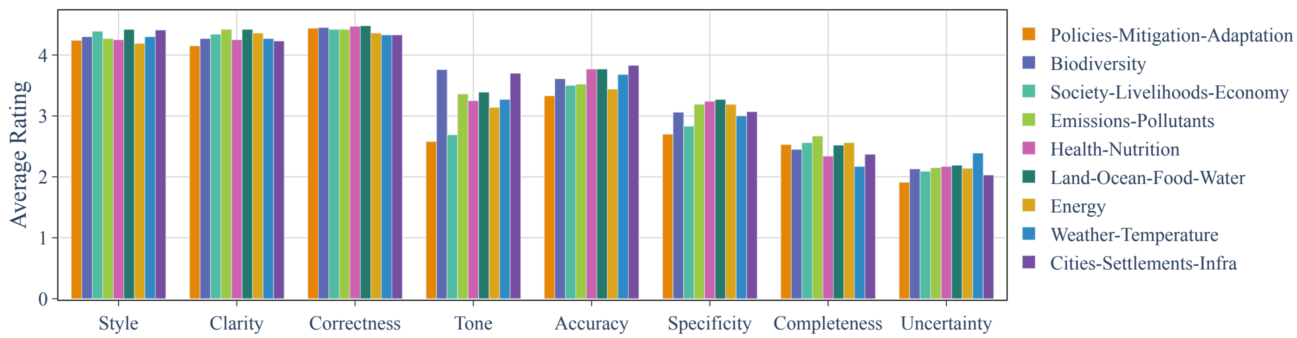


Figure 11. Average rating along all the dimensions per question topic. Questions in the *"Policies-Mitigation-Adaption"* category receive lower ratings in most of the epistemological dimensions, and particularly in "Tone" dimension.

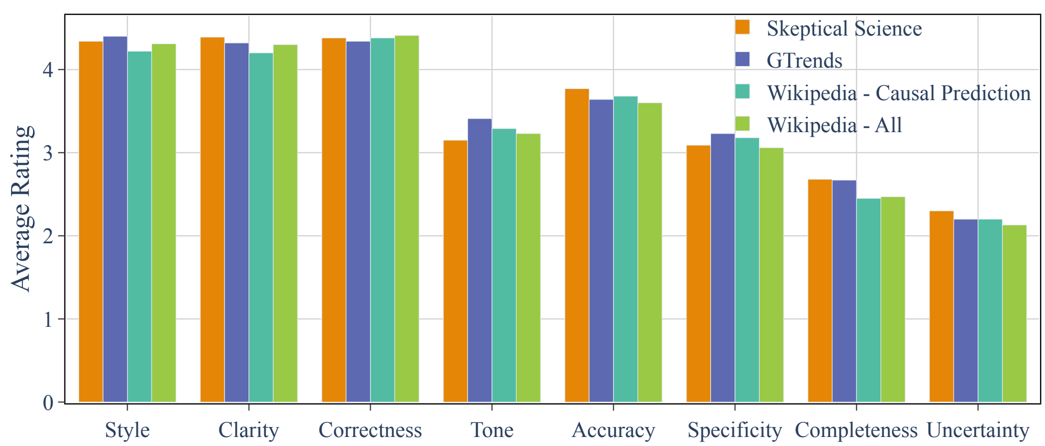


Figure 12. Average rating along all the dimensions per question source and type. In general, there is not a significant difference among the ratings based on the question source or causality.

	Without AI Assistance (3x)	With AI assistance (3x)
Any	83.33 %	93.33 %
Majority	60.00 %	76.67 %
All	33.33 %	43.33 %

Table 20. Validation results. The percentage of the (30) issues recognized by any rater, the majority of raters or all of the raters.

A.14. Validation experiments

To validate our evaluation framework, we manually created a set of 30 questions and answers, each exhibiting a specific issue from our full list of issues. We pose this as a task to our raters in two settings: with and without AI Assistance, each replicated three times.

We found (cf. Table 20) that without assistance, most of the issues (83%) were found by at least one rater, but only 60% of issues by the majority of raters.

With the help of assistance, more issues were detected (93.33% were detected by at least one rater, 76.67% by the majority of raters). There was just one issue not detected by any rater: *anecdotal evidence*[19].

[19] All raters did correctly rate the dimension ('accuracy' as 1 or 2), but highlighted only the 'incorrect' issue. The answer was incorrect, based on anecdotal evidence.

A.15. LLM Rater

We investigate the possibility of using an LLM to perform the rating task on our evaluation framework. We use `GPT-4` and prompt it using the same language as presented to the human raters (Table 21). We sample 3 responses (temperature 0.6) from `GPT-4` for each question to replicate the setup we have with human raters. We observe the following from the results in Table 22. First, `GPT-4` rater also benefits from assistance. Consistent with findings with human raters, `GPT-4` rater rates answers lower when assistance is provided. This makes sense because (1) the assistance provides an additional chain-of-thought like input and (2) the assistance is generated using additional documents which potentially provide the model with additional information. When the issues in the answers are more severe, `GPT-4` rater agrees with human raters on all dimensions, as evident in the ratings for `InstructGPT` (text-davinci-002). However, `GPT-4` rater disagrees with human raters on the relative ranking of answers from different models of similar quality. Notably, the `GPT-4` rater is more generous towards OpenAI models than humans are.

Function	Prompt
System	You are an expert on climate communication. Given a question, and an answer to it, and maybe a succinct critique of the answer.
Rating	To what extent do you agree with the following statement on the 5-point likert scale (1=disagree completely, 2=disagree, 3=neither, 4=agree, 5=agree completely)? Question: [*question*] Answer: [*answer*] Critique: [*critique*] Statement: [*statement for different dimensions (below)*] Answer in the format "Rating: X Problem: Y Explanation: Z"
Style Statement	The information is presented well (for a general audience). If you disagree, what is the problem with the answer? Choose one of the following: too informal/colloquial, answer too long, answer too short, inconsistent language/style/terminology, repetitive, other. If you choose other, please explain your rating.
Clarity Statement	The answer is clear and easy to understand. If you disagree, what is the problem with the answer? Choose one of the following: sentences too long, language too technical, numbers/formulae hard to understand, other. If you choose other, please explain your rating.
Correctness Statement	The language in the answer does not contain mistakes. If you disagree, what is the problem with the answer? Choose one of the following: sentence is incomplete, spelling mistakes, punctuation mistakes, grammatical errors, other. If you choose other, please explain your rating.
Tone Statement	The tone of the answer is neutral and unbiased. If you disagree, what is the problem with the answer? Choose one of the following: the answer is biased, tries to convince me of an opinion/belief, the tone is too negative, other. If you choose other, please explain your rating.
Accuracy Statement	The answer is accurate. If you disagree, what is the problem with the answer? Choose one of the following: incorrect, takes scientific findings out of context, self-contradictory, anecdotal, wrong use of key terms/scientific terminology, other. If you choose other, please explain your rating.
Specificity Statement	The answer addresses only what the question asks for, without adding irrelevant information. If you disagree, what is the problem with the answer? Choose one of the following: includes irrelevant parts, too vague/unspecific, other. If you choose other, please explain your rating.
Completeness Statement	The answer addresses everything the question asks for. If you disagree, what is the problem with the answer? Choose one of the following: misses important parts of the answer, does not address the region the question asks about, does not address time or time range the question asks about, does not give enough detail (e.g., numbers, statistics, details), ignores relevant scientific knowledge, other. If you choose other, please explain your rating.
Uncertainty Statement	The answer appropriately conveys the uncertainty involved. If you disagree, what is the problem with the answer? Choose one of the following: degree of (un)certainty not given when it should be, agreement in the scientific community not given when important, contradicting evidence (if existing) not mentioned, other. If you choose other, please explain your rating.

Table 21. Prompts used to generate ratings.

System	style	clarity	correctness	tone	accuracy	specificity	completeness	uncertainty
GPT4	4.71	4.89	5.00	3.88	4.13	3.66	2.97	2.05
ChatGPT	4.75	4.91	4.99	3.91	4.18	3.68	2.72	2.00
InstructGPT (davinci-003)	4.39	4.68	4.63	4.05	3.49	3.29	2.44	1.91
InstructGPT (davinci-002)	2.88	3.25	3.54	3.11	2.32	2.27	1.89	1.74
InstructGPT (turbo)	4.62	4.82	4.89	3.80	3.76	3.30	2.46	1.94
PaLM-2 (text-bison)	4.40	4.72	4.75	3.42	3.38	3.03	2.31	1.92
Falcon (180B-Chat)	4.66	4.85	4.91	3.83	4.03	3.49	2.71	2.00
GPT4, no assistance	4.70	4.89	5.00	4.77	4.95	4.59	4.59	2.63

Table 22. Results from the LLM Rater.

A.16. Timing analysis

We analyze how long raters take for their tasks. As can be seen in Figure 13, rating the epistemological dimensions generally takes more time than assessing the presentation quality, even though the latter is done first in our questionnaire. We also observe that for most systems the screening part, which includes the initial reading of question and answer, takes longer than rating the presentational dimensions. The exception to this rule are answers from *InstructGPT (davinci-002)* which are often shorter and thus quicker to read.

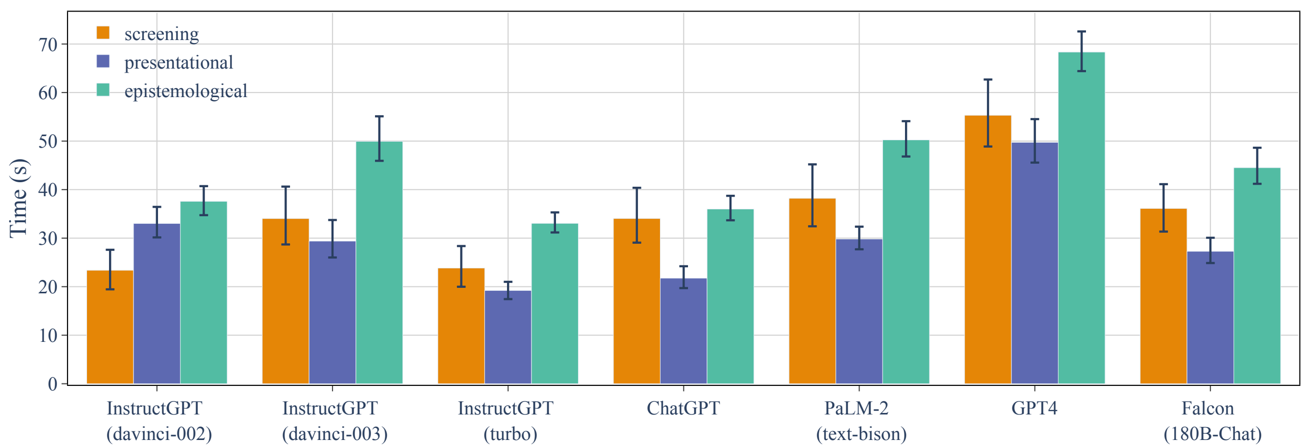


Figure 13. Average time per example for the screening, presentational, and epistemological assessment.

Figure 14 shows that *tone* seems to be harder to assess among the presentational dimensions whereas *accuracy* is quicker among the epistemological dimensions. Otherwise, each dimension takes a similar amount of time.

Larger differences are revealed when we analyze how the rating itself affects the rating times. As expected, Figure 15 shows that high ratings are quicker than lower ones. Keep in mind that for disagreeing ratings (less than 3) we also require the raters to point out specific issues which may add to the length of the interaction. Nevertheless, the trend is also clear among the better (3-5) ratings as well as *between* 1 and 2. For the epistemological dimensions the raters can also select *I don't know*, which takes slightly longer than choosing the middle rating of 3.

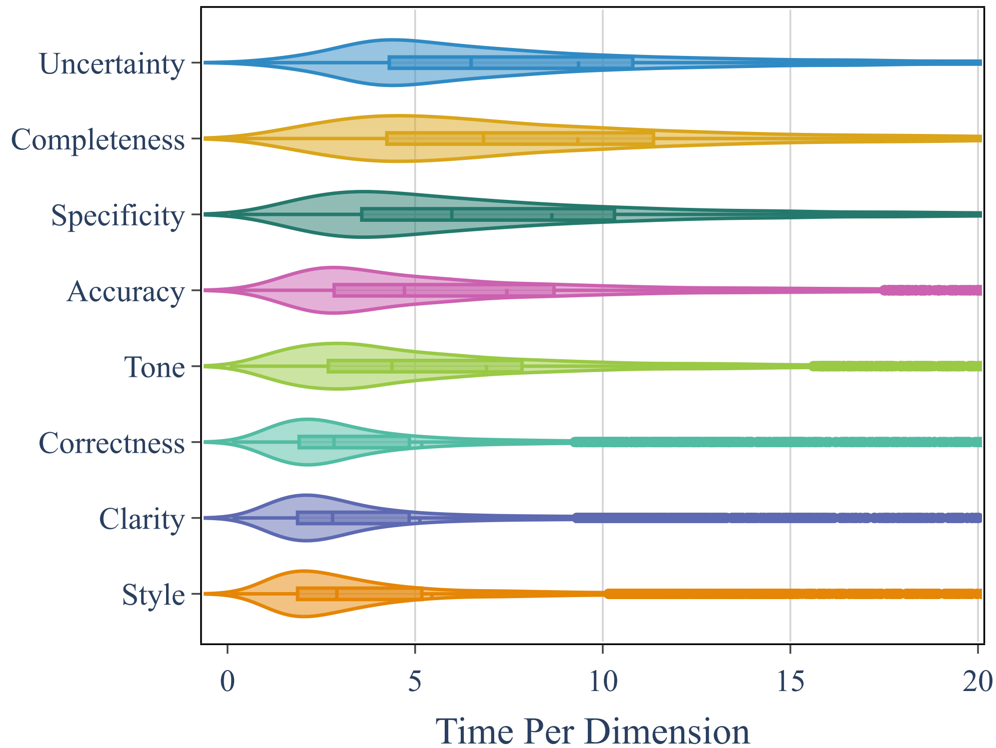


Figure 14. Distribution of rating times for presentational (style, clarity, correctness, tone) and epistemological (specificity, uncertainty, completeness, accuracy) dimensions. For ease of presentation, this figure ignores a small number of timings that took longer than $60s$.

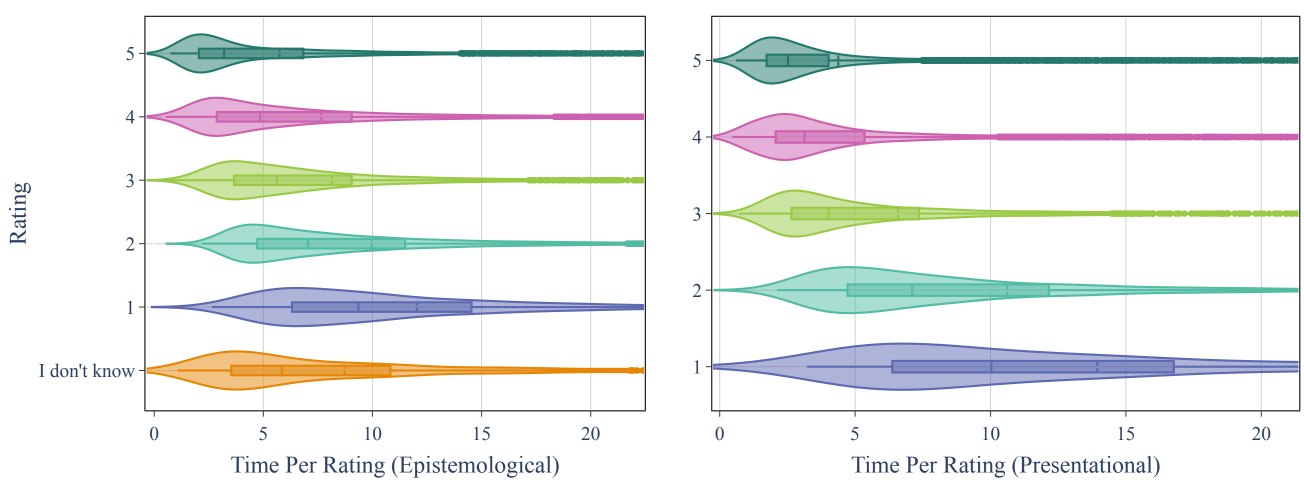


Figure 15. Average time per example for the epistemological and presentational assessment.

A.17. Answers

In this section, we present examples showing good versus bad answers for each dimension evaluated in Tables 23 to 30.

Question	In what ways can peri-urban ecosystems help reduce the urban heat island effect?	
	Model A	**Model B**
Answer	Peri-urban ecosystems can significantly help reduce the urban heat island effect in several ways. Firstly, they act as natural coolants by providing shade and releasing moisture into the atmosphere through a process known as evapotranspiration, which can lower surrounding temperatures. Secondly, these ecosystems, which include forests, grasslands, and wetlands, can absorb and store heat, reducing the overall temperature in urban areas. Lastly, they can also help mitigate the heat island effect by reducing the need for energy-intensive cooling systems, as well-vegetated areas are naturally cooler than concrete or asphalt surfaces.	Peri-urban ecosystems can help reduce the urban heat island effect by providing shade, evaporative cooling, and habitat for cooling breezes. Trees and other vegetation in peri-urban areas can help to block the sun's rays, reducing the amount of heat that is absorbed by the ground. The evaporation of water from plants and soil can also help to cool the air, and vegetation can create shade that helps to block the sun's heat. In addition, vegetation can provide habitat for animals that help to create cooling breezes. All of these factors can help to reduce the urban heat island effect, making cities more livable and sustainable.
Assistance		The answer contains repetition, specifically in the explanation of how vegetation provides shade and blocks the sun's heat.
Issues		repetitive
Rating	4.6	2.0

Table 23. Example for the **style** dimension. The Model B answer repeats the explanation on how vegetation provides shade and blocks the sun's heat.

A.18. AI Assistance

In this section, we present examples showing AI assistance that influence human ratings in Tables 31 to 35.

Question	Was the name 'global warming' changed to 'climate change'?	
	Model A	**Model B**
Answer	Yes	Yes, the term "global warming" was changed to "climate change" in order to better reflect the broader range of impacts associated with rising greenhouse gas emissions. While global warming refers specifically to the increase in Earth's average surface temperature, climate change encompasses a wider array of changes, including shifts in precipitation patterns, sea level rise, and the frequency and intensity of extreme weather events. The term "climate change" is now widely used to capture the full scope of these impacts.
Assistance	The answer lacks sufficient detail to fully address the complexity of the question.	
Issues	too_short, vague	
Rating	2.6	4.6

Table 24. Example for the **clarity** dimension. The Model A answer is too short. It lacks details and context to fully address the question.

Question	Which areas in Nigeria are at risk of rising sea levels?	
	Model A	**Model B**
Answer	The coastal areas of Nigeria are at risk of rising sea levels due to climate change. These areas include Lagos, Ogun, and Delta states. Rising sea levels could cause flooding, erosion, and salinization of freshwater sources. This could have a devastating impact on the livelihoods of the people who live in these areas.	I do not have access to the latest information on the specific areas in nigeria that are at risk of rising sea levels. however, it is important to note that nigeria, like many other countries, is vulnerable to the impacts of climate change, including sea level rise. coastal cities and communities are particularly at risk, and it is crucial for nigeria to take action to mitigate and adapt to the effects of climate change.
Assistance		The answer contains a grammatical error - "nigeria" should be capitalized as "Nigeria".
Issues		incorrect_grammar, incorrect_spelling
Rating	4.6	2.3

Table 25. Example for the **correctness** dimension. The Model B answer contains a grammatical error where the first letter of a location name should be capitalized.

Question	Do volcanos emit more CO2 than humans?	
	Model A	**Model B**
Answer	No, volcanoes do not emit more CO2 than humans. According to the U.S. Geological Survey, human activities, particularly the burning of fossil fuels for energy, emit more than 60 times the amount of carbon dioxide than volcanoes each year. While volcanoes do contribute to CO2 emissions, their contribution is relatively small compared to human activities. It's important to note that human-induced climate change is primarily driven by the increase in greenhouse gases from human activities, not natural processes like volcanic eruptions.	No, volcanoes do not emit more CO2 than humans. While volcanic eruptions do release significant amounts of CO2 into the atmosphere, the total annual emissions from volcanoes are estimated to be about 0.3 to 0.4 billion metric tons. In contrast, human activities, such as burning fossil fuels and deforestation, emit over 35 billion metric tons of CO2 annually, which is about 100 times more than volcanic emissions.
Assistance		
Issues	biased, persuasive	
Rating	2.0	4.3

Table 26. Example for the **tone** dimension. Instead of answering with only facts, the Model A answer assigns blame on human activities as the cause of climate change which was not part of the question.

Question	How does burning fossil fuels mitigate climate change	
	Model A	**Model B**
Answer	Burning fossil fuels does not mitigate climate change. In fact, it is one of the primary causes of climate change. When fossil fuels are burned, they release carbon dioxide and other greenhouse gases into the atmosphere, which trap heat and contribute to global warming. To mitigate climate change, we need to transition to cleaner, renewable sources of energy and reduce our overall energy consumption.	Burning fossil fuels releases greenhouse gases into the atmosphere, which trap heat and cause the planet to warm. This is the leading cause of climate change. However, burning fossil fuels can also be used to mitigate climate change by generating electricity from renewable sources, such as solar and wind power. This can help to reduce the amount of greenhouse gases emitted into the atmosphere and slow the rate of climate change.
AI Assistance		The critique is that the statement inaccurately suggests that burning fossil fuels can mitigate climate change. As per the provided paragraphs, "the burning of fossil fuels is the main source of greenhouse gas emissions causing global warming and ocean acidification." Furthermore, "the International Energy Agency concluded that no new fossil fuel extraction projects could be opened if the global economy and society wants to avoid the worst impacts of climate change and meet international goals for climate change mitigation." Therefore, burning fossil fuels contributes to climate change rather than mitigating it.
Issues		incorrect, science_out_of_context, self_contradictory
Rating	4.6	1.3

Table 27. Example for the **accuracy** dimension. The Model B answer contains a factual error which suggests that burning fossil fuels can mitigate climate change.

Question	What happened to global temperatures by the mid-1970s?	
	Model A	**Model B**
Answer	By the mid-1970s, global temperatures began to rise at an accelerated rate. This period marked the end of a slight cooling phase that had occurred from the 1940s to the 1970s, often referred to as the ”global cooling” period. The shift in temperature trends was largely due to increased levels of greenhouse gases, particularly carbon dioxide, in the Earth's atmosphere from human activities such as burning fossil fuels. This marked the beginning of a period of rapid global warming that continues today.	By the mid-1970s, global temperatures had risen by about 0.2 degrees Celsius (0.36 degrees Fahrenheit) since the late 19th century. This warming trend was statistically significant, and it was consistent with the predictions of climate models that had been developed in the 1960s and 1970s.
Assistance	The statement is incorrect in asserting that there are no vague or generic statements in the answer. The phrase ”increased levels of greenhouse gases, particularly carbon dioxide, in the Earth's atmosphere from human activities such as burning fossil fuels” is a generic statement that could benefit from specific data or examples. As per Wikipedia, ”The 2011–2020 decade warmed to an average 1.09 °C [0.95–1.20 °C] compared to the pre-industrial baseline (1850–1900). Surface temperatures are rising by about 0.2 °C per decade, with 2020 reaching a temperature of 1.2 °C above the pre-industrial era.” This specific information could enhance the answer's clarity and precision.	The answer could be improved by including the specific information that ”The 2011–2020 decade warmed to an average 1.09 °C [0.95–1.20 °C] compared to the pre-industrial baseline (1850–1900)” and ”Surface temperatures are rising by about 0.2 °C per decade,” which provides a more precise context for the warming trend observed by the mid-1970s.
Issues	vague	
Rating	2	4

Table 28. Example for the **specificity** dimension. The Model A answer omits specific numbers on how much the global temperatures have changed which is important for the answer's clarity and precision.

Question	How much do cows contribute to climate change	
	Model A	**Model B**
Answer	Cows significantly contribute to climate change due to the production of methane, a potent greenhouse gas, during their digestion process. According to the United Nations' Food and Agriculture Organization, livestock (including cows) account for about 14.5% of all human-caused greenhouse gas emissions, with cows being the largest contributor. This is equivalent to the exhaust emissions from all the vehicles on the planet. Therefore, the impact of cows on climate change is substantial and cannot be overlooked.	Cows are a major source of methane, a powerful greenhouse gas that contributes to climate change. According to the Environmental Protection Agency (EPA), cattle and other livestock are responsible for about 5.5 percent of all human-caused greenhouse gas emissions.
Assistance	While the answer provides a comprehensive overview of cows' contribution to climate change, it fails to mention the potential for mitigation efforts, such as the adoption of best practices that can reduce emissions by up to 30%, as stated by the FAO. Furthermore, it does not address the variability in environmental impacts due to different agricultural practices around the world.	While the answer provides a general overview of the contribution of cows to climate change, it fails to mention the potential mitigation strategies, such as dietary changes and adoption of best practices, which can significantly reduce emissions. As stated in the provided paragraphs, "Mitigation options for reducing methane emission from livestock include a change in diet, that is consuming less meat and dairy" and "FAO estimates that the adoption of already available best practices can reduce emissions by up to 30%".
Issues		not_enough_detail, does_not_address_main_parts, ignores_science
Rating	4.6	2

Table 29. Example for the **completeness** dimension. The Model B answer lacks context and details around the answer. The assistance on missing mitigation efforts is not helpful because it is not necessary to make the answer complete. The raters are able to recognize this and give Model A answer a correct high rating.

Question	Did Hansen predict that the West Side highway would be underwater in 20 years?	
	Model A	**Model B**
Answer	James Hansen, a prominent climate scientist, did make a statement in a 1988 interview suggesting that the West Side Highway in New York City could be underwater in 40 years. However, this was not a formal prediction based on a specific scientific study, but rather a speculative comment made to illustrate potential impacts of climate change. It's important to note that while sea levels are indeed rising due to climate change, the exact rate and impact can vary greatly depending on a range of factors, including greenhouse gas emissions and ice melt rates.	No, Hansen did not predict that the West Side highway would be underwater in 20 years. He did, however, predict that sea levels would rise by about 2 feet by 2100, which would put the West Side highway at risk of flooding.
Assistance	The statement overlooks the importance of communicating uncertainty in climate science. As per the answer, Hansen's comment was speculative and not based on a specific study, thus it's crucial to mention this uncertainty to avoid misinterpretation of the potential impacts of climate change.	The statement fails to acknowledge that the answer does not explicitly convey the inherent uncertainty in climate predictions, such as Hansen's prediction about sea level rise. According to Wikipedia, "Uncertainty is a fundamental characteristic of weather, seasonal climate, and hydrological prediction, and no forecast is complete without a description of its uncertainty."
Issues		uncertainty_missing
Rating	4	2.3

Table 30. Example for the **uncertainty** dimension. The Model B answer states precise predictions without acknowledging the uncertainty in climate science as there are many factors that can influence a prediction.

Question	Is IPCC consensus phoney?
Answer	No, the consensus of the Intergovernmental Panel on Climate Change (IPCC) is not phoney. The IPCC is a reputable international body that assesses the science related to climate change. It was established by the United Nations Environment Programme (UNEP) and the World Meteorological Organization (WMO) in 1988 to provide policymakers with regular scientific assessments on climate change, its implications and potential future risks, as well as to put forward adaptation and mitigation strategies. The consensus reached by the IPCC is based on rigorous scientific research and review by experts from all over the world, making it a reliable and authoritative source of information on climate change.
Assistance	The tone of the answer, while factual, may be perceived as biased due to the strong defense of the IPCC's credibility and authority.
Rating with Assistance	2.3 [biased, persuasive]
Rating without Assistance	4.6

Table 31. Example for the **tone** dimension. Raters identify the biased tone only with assistance.

Question	How do single-family houses contribute to higher toxic chemical emissions compared to multifamily buildings?
Answer	Single-family houses contribute to higher toxic chemical emissions compared to multifamily buildings primarily due to their larger size and individualized systems. Each single-family home typically has its own heating, cooling, and water systems, all of which consume energy and produce emissions. Additionally, these houses often have larger lawns requiring maintenance equipment like lawnmowers and leaf blowers, which also emit harmful chemicals. Lastly, single-family homes, due to their larger size, require more materials to build and maintain, leading to higher emissions from the production and transportation of these materials.
Assistance	While the answer provides a plausible explanation, it lacks empirical evidence or scientific findings to support the claim that single-family houses contribute to higher toxic chemical emissions compared to multifamily buildings.
Rating with Assistance	1.6 [anecdotal, incorrect, science_out_of_context]
Rating without Assistance	4

Table 32. Example for the **accuracy** dimension. Raters identify the anecdotal nature of the answer only with assistance.

Question	Are climate change solutions too expensive?
Answer	While it's true that implementing solutions to combat climate change requires significant financial investment, it's important to consider the cost of inaction, which is likely to be much higher. The economic damage caused by extreme weather events, rising sea levels, and other climate-related impacts could be devastating. Moreover, many climate solutions, such as renewable energy technologies, are becoming increasingly cost-competitive. Investing in these solutions can also stimulate economic growth and create jobs, providing a return on investment. Therefore, while the upfront costs may be high, the long-term benefits both economically and environmentally make it a necessary investment.
Assistance	The statement is incorrect as the answer contains a vague statement. The phrase "the cost of inaction, which is likely to be much higher" is not quantified or supported with specific data or examples. As per the provided Wikipedia paragraphs, "a 2021 study by the reinsurance company Swiss Re estimated global climate change is likely to reduce global economic output by 11-14%, or as much as $23 trillion annually by 2050, compared with output without climate change." This specific information could have been used to substantiate the claim.
Rating with Assistance	2 [vague, irrelevant_info]
Rating without Assistance	4.6

Table 33. Example for the **specificity** dimension. Raters identify how specific information could make the answer better only with assistance.

Question	Is the Arctic ice melt a natural cycle?
Answer	While the Arctic ice does go through natural cycles of melting and refreezing, the accelerated rate of ice melt that we are currently witnessing is not part of a natural cycle. Scientific evidence overwhelmingly points to human-induced climate change as the primary cause. Rising global temperatures, largely due to greenhouse gas emissions from human activities, are causing the Arctic ice to melt at an unprecedented rate. This rapid ice loss is having profound effects on Arctic ecosystems and contributing to rising sea levels globally.
Assistance	While the answer provides a comprehensive explanation of the Arctic ice melt, it lacks specific details such as the decline rate of 4.7% per decade, the projection of the first ice-free conditions around 2035 under a scenario of continually accelerating greenhouse gas emissions, and the fact that Arctic ice decline between 1979 and 2011 is estimated to have been responsible for as much radiative forcing as a quarter of CO2 emissions the same period.
Rating with Assistance	2 [not_enough_detail]
Rating without Assistance	5

Table 34. Example for the **completeness** dimension. Raters identify how specific information could make the answer better only with assistance.

Question	will global warming cause an ice age
Answer	While it may seem counterintuitive, some scientists have suggested that global warming could potentially trigger what's known as a "mini ice age." This theory is based on the idea that increased melting of polar ice could disrupt ocean currents, such as the Gulf Stream, that play a crucial role in regulating global climate. If these currents were to be significantly altered or shut down, it could potentially lead to a dramatic cooling of certain regions, such as Northern Europe. However, this is just one theory and the overall consensus among scientists is that global warming will lead to a general trend of increasing temperatures worldwide.
Assistance	While the answer acknowledges the theory of a potential "mini ice age" due to global warming, it fails to adequately convey the scientific consensus on the matter. As stated in the provided paragraphs, "Earth system models used in Coupled Model Intercomparison Project indicate that shutdown is only likely after high levels of warming are sustained well after 2100," and "paleoceanographic research suggests that the AMOC may be even more stable than what is predicted by most models." Therefore, the answer could mislead readers into thinking that a "mini ice age" is a more immediate and likely consequence of global warming than what is generally agreed upon by the scientific community.
Rating with Assistance	1.6 [uncertainty_missing, consensus_missing, contradicting_evidence_missing]
Rating without Assistance	4.6

Table 35. Example for the **uncertainty** dimension. Raters identify the unlikelihood of the theory only with assistance.