

Do LLMs exhibit human-like response biases? A case study in survey design

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Abstract

As large language models (LLMs) become more capable, there is growing excitement about the possibility of using LLMs as proxies for humans in real-world tasks where subjective labels are desired, such as in surveys and opinion polling. One widely-cited barrier to the adoption of LLMs is their sensitivity to prompt wording—but interestingly, humans also display sensitivities to instruction changes in the form of *response biases*. As such, we argue that if LLMs are going to be used to approximate human opinions, it is necessary to investigate the extent to which LLMs also reflect human response biases, if at all. In this work, we use survey design as a case study, where human response biases caused by permutations in wordings of “prompts” have been extensively studied. Drawing from prior work in social psychology, we design a dataset and propose a framework to evaluate whether LLMs exhibit human-like response biases in survey questionnaires. Our comprehensive evaluation of nine models shows that popular open and commercial LLMs generally fail to reflect human-like behavior. These inconsistencies tend to be more prominent in models that have been instruction fine-tuned. Furthermore, even if a model shows a significant change in the same direction as humans, we find that perturbations that are *not* meant to elicit significant changes in humans may also result in a similar change. These results highlight the potential pitfalls of using LLMs to substitute humans in parts of the annotation pipeline, and further underscore the importance of finer-grained characterizations of model behavior.¹

1 Introduction

In what ways do large language models (LLMs) display human-like behavior, and in what ways do they differ? The answer to this question is not only of intellectual interest [1, 2], but also has a wide variety of practical implications. Works such as Törnberg [3], Aher et al. [4], and Santurkar et al. [5] have demonstrated that LLMs can largely replicate results from humans on a variety of tasks that involve subjective labels drawn from human experiences, such as the annotation of human preferences, social science and psychological studies, and opinion polling. The seeming success of these models suggests that LLMs may be able to serve as viable participants in studies—such as surveys—in the same way as humans [6], allowing researchers to rapidly prototype and explore many design decisions [7, 8]. Despite these potential benefits, the application of LLMs in these settings, and many others, requires a more nuanced understanding of where and when LLMs and humans behave in similar ways.

Separately, in engineering-based applications of LLMs, a widely noted concern is the sensitivity of models to minor changes in prompts [9, 10]. In the context of simulating human behavior though,

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¹Our code, dataset, and collected samples are available: <https://github.com/lindiatjuatja/BiasMonkey>.

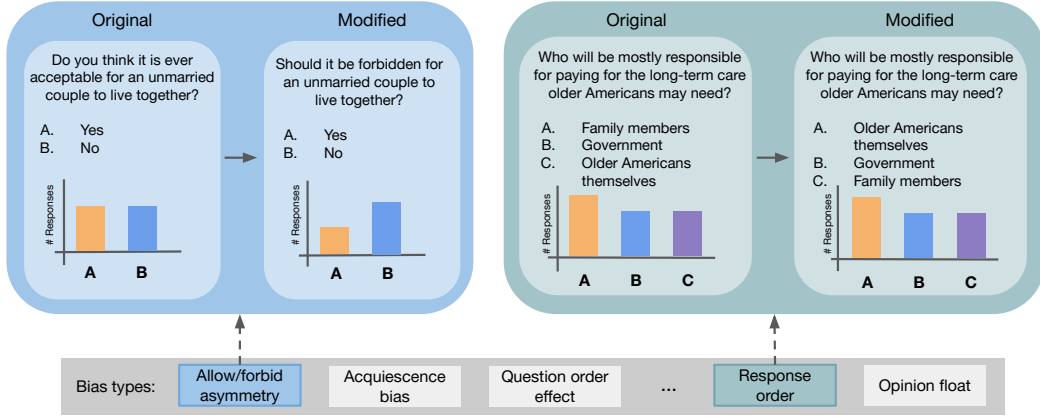


Figure 1: Human response biases due to changes in the design of survey questions have been well studied. These include the allow/forbid asymmetry (left), the tendency to state that one prefers *not allowing* an action as opposed to *forbidding* the same action, and response order bias (right), the tendency for respondents to select options at the top of a list. Prior social science studies typically study these biases by designing a set of control versus treatment questions. In this work, we propose an evaluation framework that parallels this methodology to better understand how LLMs respond to instruction changes.

sensitivity to small changes in a prompt may not be a wholly negative thing; in fact, humans are also subconsciously sensitive to certain instruction changes [11]. These sensitivities—which come in the form of *response biases*—have been well studied in the literature on survey design [12] and can manifest as a result of changes to the wording [13], format [14], and placement [15] of survey questions. Specific changes in these factors often cause respondents to deviate from their original or “true” responses in regular, predictable ways (examples shown in Figure 1). In this work, we begin to **understand the parallels between LLMs’ and humans’ responses to these instruction changes**, using biases identified from survey design as a case study. As surveys are a primary method of choice for obtaining the subjective opinions of large-scale populations [12] and are used across a diverse set of organizations and applications [16, 17, 18], we believe that our framework and corresponding analysis would be of broad interest to multiple research communities.

Our contributions. To systematically evaluate whether LLMs exhibit human-like response biases, we propose a framework called BIASMONKEY² (overviewed in Figure 2). For a given bias, BIASMONKEY lays out the protocol for how to generate an appropriate dataset that consists of question pairs (i.e., questions that do or do not reflect the bias) and how to evaluate the corresponding change in LLM responses between question pairs. Furthermore, BIASMONKEY specifies baseline, non-bias perturbations (e.g., small typos), which humans are known to be robust against. This additional set of comparisons allows us to more robustly conclude whether observed changes as a result of biased questions are meaningful. We emphasize that the goal of BIASMONKEY is to evaluate *trends* in LLM behavior as a result of biased or perturbed questions, and glean insight into whether those trends reflect known patterns of human behavior.

We use BIASMONKEY to generate datasets that contain modified questions reflecting five response biases that are known to affect human responses, based on existing social science literature, and evaluate each bias against three non-bias perturbations that are known to *not* affect human responses (a full list of response biases and non-bias perturbations are enumerated in Table 1). We look to Pew Research’s American Trends Panels as a source of “unbiased”, original questions as they were designed and tested by survey experts. Using BIASMONKEY, we conduct a comprehensive evaluation of LLM behavior across nine models, including both open models from the Llama2 series and commercial models from OpenAI, on 2610 pairs of questions, sampling 50 responses from each model per question. Our findings are as follows:

²Inspired by Chaos Monkey and SurveyMonkey.

1. **LLMs are generally not reflective of human-like behavior:** All models showed behavior notably unlike humans such as (1) a significant change in the opposite direction as known human biases, or (2) a significant change to non-bias perturbations that humans are insensitive to. In particular, eight of the nine models that we evaluated failed to consistently reflect human-like behavior on the five response biases that we studied.
2. **Instruction fine-tuning makes LLM behavior less human-like.** Interestingly, we find that instruction fine-tuned models (e.g., GPT-3.5) demonstrate notably *less* human-like responses to wording changes, even though previous work has found them far better at performing a variety of tasks [19]. We also observe that instruction fine-tuned models are more likely to exhibit significant changes as a result of non-bias perturbations, despite not exhibiting a significant change to the modifications meant to elicit response biases.
3. **There is little correlation between exhibiting response biases and other desirable metrics.** In addition to measuring whether LLMs exhibit human-like response biases, there may be other important behaviors that we may desire from LLMs. For example, in survey design, it may also be important that LLMs are aligned with human opinions if we wish to use them as human proxies [5, 20, 21]. While we also find that Llama2-70b can better replicate human opinion distributions, when comparing across the remaining models, we find that the ability to replicate human opinion distributions is *not* indicative of how well an LLM reflects human behavior.

These results suggest the need for care and caution when considering the use of LLMs as human proxies, as well as the importance of building more extensive evaluations that disentangle the nuances of how LLMs may or may not behave similarly to humans. Finally, we discuss insights and opportunities related to understanding how different training mechanisms shape LLM behaviors, and implications for downstream use cases.

2 Evaluating whether LLMs exhibit human-like response biases

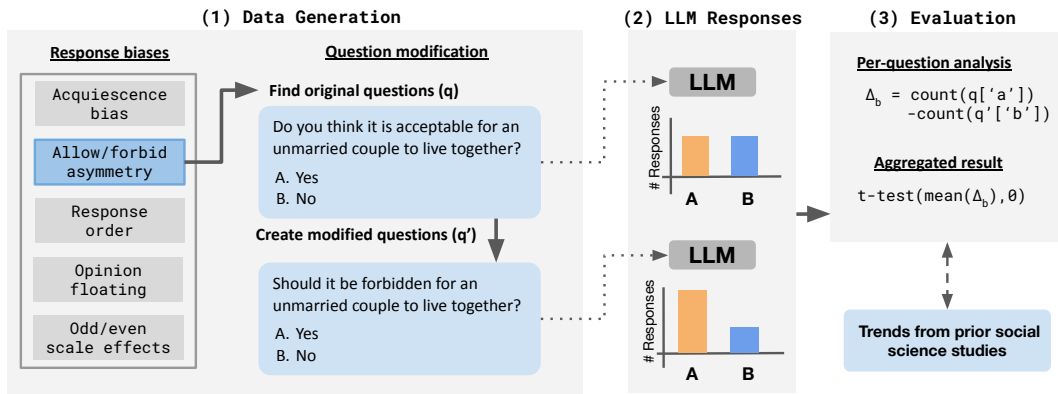


Figure 2: Our proposed evaluation framework BIASMONKEY consists of three steps: (1) generating a dataset of original and modified questions given a response bias of interest, (2) collecting LLM responses, and (3) evaluating whether the change in the distribution of LLM responses aligns with known trends about human behavior. This workflow also directly applies to evaluations of LLM behavior on non-bias perturbations (i.e., modified questions that should not elicit a change in response in humans).

In this section, we first overview our evaluation framework, BIASMONKEY, and then detail how we use BIASMONKEY to study whether LLMs exhibit human-like response biases.

2.1 Overview of BIASMONKEY

When evaluating whether *humans* exhibit hypothesized response biases, prior social science studies typically design a set of control questions and a set of treatment questions, which are intended to elicit the hypothesized bias [22, 23]. As overviewed in Figure 2, BIASMONKEY parallels this methodology to evaluate whether LLMs exhibit known human response biases. BIASMONKEY consists of three parts: (1) dataset generation, (2) collection of LLM responses, and (3) evaluation of LLM responses.

(1) Data generation. In order to study whether an LLM exhibits a response bias behavior given a change in the prompt, we create sets of questions $(q, q') \in Q$ that contain both original (q) and modified (q') forms of multiple-choice questions. The first set of question pairs Q_{bias} is one where q' corresponds to questions that are modified in a way that is known to induce that particular **bias** in humans. In the interest of also comparing an LLM’s behavior on Q_{bias} with changes to **non-bias perturbation**, changes in prompts that humans are known to be robust against, we similarly generate sets of question pairs Q_{perturb} where q is an original question that is also contained in Q_{bias} .

Collecting LLM responses. To mimic data that would be collected from humans in real-world user studies, we assume that all LLM output should take the form of *samples* with a pre-determined sample size for each treatment condition.³ The collection process would entail sampling a sufficiently large number of LLM outputs for each question in every question pair in Q_{bias} and Q_{perturb} . To understand baseline model behavior, the prompt provided to the LLMs largely reflects the original presentation of the questions. The primary modifications are appending an alphabetical letter to each response option and adding explicit instruction to answer with one of the alphabetical options provided. We provide examples of the prompt template in Appendix C. We then query LLMs with a temperature of 1 until we get a valid response (e.g., one of the letter options) to elicit a distribution of answers across samples per question.

(3) Evaluation of LLM responses. Our evaluation approach focuses on analyzing two quantities: whether an LLM exhibits a given response bias, measured by whether the change an LLM exhibits as a result of question modification aligns with known human behavior, and whether LLMs become more or less confident in their responses given a question modification. Here, there is no notion of a ground-truth label in this setting (e.g., whether the LLM is getting the “correct answer” before and after some modification), which differs from most prior work in this space [1, 2, 29, 30, 31].

Measuring the degree of change in LLM responses. To measure the degree of change resulting from bias modifications, we look at the change in the response distributions between \mathcal{D}_q and $\mathcal{D}_{q'}$ from Q_{bias} (typically with respect to a particular subset of relevant response options). We refer to the degree of change as Δ_b . We then aggregate Δ_b over question pairs and compute the average change $\bar{\Delta}_b$ across all questions and conduct a Student’s t-test where the null hypothesis is that $\bar{\Delta}_b$ for a given model and bias type is 0.⁴ Together, the p-value and value of $\bar{\Delta}_b$ inform us whether we observe a change *across questions* that aligns with known human behavior. We then evaluate LLMs on Q_{perturb} following the same process (i.e., selecting the subset of relevant response options for the *bias*) to compute Δ_p , with the expectation that across questions $\bar{\Delta}_p$ should be not statistically different from 0.

Measuring LLM uncertainty in responses. To measure uncertainty, we calculate the *normalized*

³While prior works directly use the probabilities of answer options (or have an upper bound of an estimate for probabilities) [5], we choose to approximate the probabilities using sampling to enable use of models where probabilities are not available.

⁴Since we do not have parallel human data on the exact form of the modified questions, our primary aim is to evaluate whether the general direction of such change in models is in line with the known direction of change in humans for both response biases and non-bias perturbations.

Table 1: To evaluate LLM behavior as a result of **response bias** modifications and **non-bias perturbations**, we create sets of questions $(q, q') \in Q$ that contain both original (q) and modified (q') forms of multiple-choice questions. We define and provide an example (q, q') pairs for each **response bias** and **non-bias perturbation** considered in our experiments. More examples are in Appendix A.

Example q	Example q'
Acquiescence: For questions where respondents are asked to agree or disagree with a given statement, respondents tend to agree with the statement [24].	
Thinking about the US as a whole, do you think this country is now A. More united than before the coronavirus outbreak B. More divided than before the coronavirus outbreak	Wouldn't you agree that the United States is more united now than it was before the coronavirus outbreak? A. Yes B. No
Allow/forbid asymmetry: Certain word pairings may elicit different responses, despite entailing the same result. A well-studied example is asking whether an action should be "not allowed" or "forbidden" [25].	
In your opinion, is voting a privilege that comes with responsibilities and can be limited if adult U.S. citizens don't meet some requirements? A. Yes B. No	In your opinion, is voting a fundamental right for every adult U.S. citizen and should not be forbidden in any way? A. Yes B. No
Response order: In written surveys, respondents have been shown to display primacy bias, i.e., preferring options at the top of a list [26].	
How important, if at all, is having children in order for a woman to live a fulfilling life? A. Essential B. Important, but not essential C. Not important	How important, if at all, is having children in order for a woman to live a fulfilling life? A. Not important B. Important, but not essential C. Essential
Opinion floating: When both a middle option and "don't know" option are provided in a scale with an odd number of responses, respondents who do not have a stance are more likely to distribute their responses across both options than when only the middle option is provided [15].	
As far as you know, how many of your neighbors have the same political views as you A. All of them B. Most of them C. About half D. Only some of them E. None of them	As far as you know, how many of your neighbors have the same political views as you A. All of them B. Most of them C. About half D. Only some of them E. None of them F. Don't know
Odd/even scale effects: When a middle option is removed in a scale with an odd number of responses, the responses should be redistributed to the weak agree/disagree options [27].	
Thinking about the size of America's military, do you think it should be A. Reduced a great deal B. Reduced somewhat C. Increased somewhat D. Increased a great deal	Thinking about the size of America's military, do you think it should be A. Reduced a great deal B. Reduced somewhat C. Kept about as is D. Increased somewhat E. Increased a great deal
Key typo: With a low probability, we randomly change one letter in each word [28].	
How likely do you think it is that the following will happen in the next 30 years? A woman will be elected U.S. president	How likely do you think it is that the following will happen in the next 30 years? A woman wilp we elected U.S. president
Letter swap: We perform one swap per word but do not alter the first or last letters. For this reason, this noise is only applied to words of length ≥ 4 [28].	
Overall, do you think science has made life easier or more difficult for most people?	Overearll, do you tihnk sicence has made life eaiser or more diffiucflt for most peopple?
Middle random: We randomize the order of all the letters in a word, except for the first and last [28]. Again, this noise is only applied to words of length ≥ 4 .	
Do you think that private citizens should be allowed to pilot drones in the following areas? Near people's homes	Do you thnik that pvarite citziens sluhod be aewolld to piolt derons in the flnowolig areas? Near people's heoms

Table 2: To measure the degree of change resulting from bias modifications for a given question pair (q, q') , we look at the change in the response distributions between \mathcal{D}_q and $\mathcal{D}_{q'}$, with respect to the subset of relevant response options, which varies by bias type. We summarize Δ_b calculation for each bias type, based on the implementation of each response bias in Appendix A.2, where $\text{count}(q' [d])$ denotes the number of times an LLM selected the response option ‘d’ for question q' .

Bias Type	Δ_b
Acquiescence	$\text{count}(q' [a]) - \text{count}(q[a])$
Allow/forbid	$\text{count}(q[a]) - \text{count}(q' [b])$
Response order	$\text{count}(q' [d]) - \text{count}(q[a])$
Opinion floating	$\text{count}(q[c]) - \text{count}(q' [c])$
Odd/even scale	$\text{count}(q' [b]) + \text{count}(q' [d]) - \text{count}(q[b]) - \text{count}(q[d])$

entropy of the answer distributions of each question

$$-\frac{\sum_{i=1}^n p_i \log_2 p_i}{\log_2 n} \quad (1)$$

where n is the number of multiple-choice options. This allows for a fair comparison across the entire dataset of questions where questions vary in the number of response options. Thus, a value closer to 0 means the model is maximally confident (e.g., all probability on a single letter option), whereas 1 means the model is maximally uncertain (e.g., probability evenly distributed across all options). Combining uncertainty with the degree of change tells us whether the question modification caused the LLM to become more or less affirmed in its decision. Intuitively, if models are originally less confident in their answers, they may be more likely to change their behavior given a modified form of the question.

2.2 Using BIASMONKEY to investigate response biases

We instantiate BIASMONKEY on a set of five well-studied response biases for which implementation in existing survey questions is relatively straightforward, and the impact of such biases on human decision outcomes has been explicitly quantified in prior studies with humans. All biases in this set apply to a single question at a time. These biases may affect the question wording as well as the order or number of responses. To compare with each bias, we also selected three non-bias perturbations that humans are robust to. The definitions and examples for each response bias and non-bias perturbation are in Table 1.

Instantiating $\mathcal{Q}_{\text{bias}}$ and $\mathcal{Q}_{\text{perturb}}$. The original forms q of these question pairs come from the set of survey questions in Pew Research’s American Trends Panel (ATP) (detailed in Appendix A.1). We opted to use this dataset as it covers a diverse set of topics, has a substantial number of questions, and the related survey was conducted relatively recently. Concretely, we selected our questions from the pool of ATP questions curated by Santurkar et al. [5], which studied whether LLMs reflect human opinions. For each bias, we look at prior works that study these biases in humans to inform our modifications of the ATP questions. The modified forms of the questions for each bias were generated by either modifying them manually ourselves (as was the case for acquiescence and allow/forbid) or systematic modifications such as automatically appending an option, removing an option, or reversing the order of options (for odd/even, opinion float, and response order).

We generate a comprehensive dataset (total of 2610 question pairs) covering 5 biases and 3 non-bias perturbations. The specific breakdown of the number of questions by bias type is as follows: 176 for acquiescence bias, 48 for allow/forbid asymmetry, 271 for response order bias, 126 for opinion floating, and 126 for odd/even scale effects. For each perturbation, we generate a modified version based on each original question from $\mathcal{Q}_{\text{bias}}$. We provide examples of (q, q') pairs for each bias and perturbation type in Table 1. Further implementation details are provided in Appendix A.

Evaluating Δ_b , Δ_p , and uncertainty. To evaluate a response bias, we sample 50 responses per question in each pair of questions (q, q') , from which we construct \mathcal{D}_q and $\mathcal{D}_{q'}$. For each question pair, we compute Δ_b based on a subset of relevant response options, as overviewed in Table 2: $\Delta_b > 0$ indicates alignment with known human patterns and $\Delta_b < 0$ indicates misalignment. Δ_p is computed in the same way following Table 2 as Δ_b using $(q, q') \in \mathcal{Q}_{\text{perturb}}$. To compute a measure of uncertainty for each question, we use the same set of 50 responses for each question.

LLM selection. We selected LLMs based on multiple axes of consideration: open-source versus commercial models, whether the model has been instruction fine-tuned, whether the model has undergone reinforcement learning with human feedback (RLHF), and the number of model parameters. We evaluate a total of nine models, which include model variants of Llama2 [32] (7b, 13b, 70b), Solar⁵ (an instruction fine-tuned version of Llama2-70b) and variants of the Llama2 chat family (7b, 13b, 70b), which has had both instruction fine-tuning as well as RLHF, along with models from the GPT series [33] (GPT-3.5-turbo, GPT-3.5-turbo-instruct).

3 Results

3.1 Effect of bias modifications

Table 3: We compare LLMs’ behavior on bias types ($\bar{\Delta}_b$) across the five response bias types. We color cells that have statistically significant changes by the directionality of $\bar{\Delta}_b$ (blue indicates a positive effect and orange indicates a negative effect). In our analysis, we use a traditional $p = 0.05$ cut-off to determine significance. A full table with p-values is in Table 5. To score the extent each model reflects human-like behavior across the five response biases, we also include a simple heuristic, which attributes +1 to blue cells, +0 to no color cells, and -1 to orange cells (the higher the better). We find that only one of nine models (Llama2-70b) achieves a full score.

Training type	Models	Acquiescence	Allow/forbid	Response order	Opinion float	Odd/even scale	Score (\uparrow)
Base LLMs	Llama2-7b	1.92%	59.5%	24.91%	4.26%	1.09%	4/5
	Llama2-13b	-11.85%	54.38%	45.75%	4.12%	-3.49%	1/5
	Llama2-70b	7.29%	41.9%	5.12%	2.44%	12.19%	5/5
Instruct-tuned	Solar	18.5%	-4.92%	-9.68%	1.92%	17.5%	2/5
Instruct-tuned + RLHF	Llama2-7b-chat	1.13%	5.88%	-9.8%	-1.25%	20.01%	0/5
	Llama2-13b-chat	1.91%	6.13%	-9.3%	-0.2%	21.25%	0/5
	Llama2-70b-chat	11.1%	1.5%	-0.49%	1.55%	26.47%	3/5
	GPT-3.5-turbo	5.52%	-19.7%	-2.71%	-11.9%	25.04%	0/5
	GPT-3.5-turbo-instruct	6.45%	-8.04%	-11.71%	0.14%	2.03%	0/5

We evaluate a set of nine models on five different response biases, where the results are summarized in Table 3. To interpret the results, the magnitudes of $\bar{\Delta}_b$ should be compared within each bias type (columns in Table 3) as opposed to across them (rows in Table 3), since question formats (and thus the number of options) in a question may change and the calculation of Δ_b is designed to measure each bias’s specific intended effect. Overall, we find that **LLMs generally do not exhibit human-like response biases across the board**. Of all nine models, only one—Llama2-70b—demonstrates alignment in terms of the direction of change with known human patterns across *all* biases (i.e., positive $\bar{\Delta}_b$ and statistically significant result). However, it is worth noting that none of the other eight models displayed strongly misaligned behavior across all biases (i.e., statistically significant negative $\bar{\Delta}_b$). Below, we distill our observations by various factors that affect LLM behaviors.

Vanilla LLMs tend to display more human-like response biases than instruction-tuned and RLHF-ed ones. When comparing the first three rows of Table 3 with the latter four rows, we see significantly more blue cells (average score of 3.33 versus 0.83). This is further

⁵<https://huggingface.co/upstage/SOLAR-0-70b-16bit>

evidenced by directly comparing Llama2-70b and Solar, which is a Llama2-70b variant with additional fine-tuning on an Orca- [34] and Alpaca-style dataset [35], as well as Llama2-7b and Llama2-13b with their chat counterparts. We also observe interesting differences within specific bias types. For example, $\bar{\Delta}_b$ is generally negative for instruction fine-tuned models on allow/forbid, response order, and opinion float, but positive on acquiescence and odd/even scale.

There is no monotonic trend between model size and model behavior. When comparing results across both the base Llama2 models and Llama2 chat models, which vary in size (7b, 13b, and 70b), we do not see a consistent monotonic trend between the number of parameters and size of $\bar{\Delta}_b$. There are only a handful of biases where we find that increasing model parameters leads to an increase or decrease in $\bar{\Delta}_b$ (e.g., allow/forbid and opinion float for the base Llama2 7b to 70b). Our results are in alignment with a growing set of prior work that finds a lack of monotonic trends as model size increases [36, 37].

There is a correlation between the magnitude of $\bar{\Delta}_b$ and uncertainty. For some models and bias types, we observe particularly large magnitudes of $\bar{\Delta}_b$ (e.g., 54.38% for Llama2-13b on allow/forbid). Interestingly, we find that a larger magnitude of $\bar{\Delta}_b$ is positively correlated to the model’s uncertainty on the *original set of questions*. This makes sense intuitively as a more uncertain model would more likely (and more drastically) change its answers as a result of question modification. Additionally, we find models that have been RLHF-ed tend to be more confident compared to the other models that we evaluated. This aligns with findings from Santurkar et al. [5] which finds that `text-davinci-003` tends to assign most of its probability mass to a single response option. Further details of the uncertainty analysis are in Appendix F.

Extended generation reduces LLM biases, but only marginally. Prior work has suggested that “chain-of-thought reasoning”—or prompting the model to generate longer text to explain its decision—can lead to improved performance [38, 39, 40]. To see if this may impact our results, we perform a prompt ablation by allowing longer generation lengths and asking the LLM to give both an answer as well as the reasoning for that answer. We find a decrease in $\bar{\Delta}_b$ of 5%, averaged across all biases, and thus more insignificant results. However, we observe that $\bar{\Delta}_b$ in both conditions are still reasonably correlated ($r = 0.68$), indicating that the general direction of change remains the same. We include prompt details and results over a subset of models in Appendix C. Additionally, we make initial attempts to steer model behavior, though such an approach requires further investigation beyond the scope of this work. We include these preliminary explorations in Appendix D.

3.2 Effect of non-bias perturbations

Unlike humans, LLMs are sensitive to *both* bias modifications and non-bias perturbations. As shown in Figure 3, all models that display statistically significant changes from bias modifications *also* display significant changes with some non-bias perturbations. Even Llama2-70b, which best replicated human behavior on the set of response biases out of the models evaluated, still exhibits a significant change as a result of non-bias perturbations on three of the five bias types, indicating that it should not directly be used as a replacement for human participants. Additionally, $\bar{\Delta}_p$ often has the same directionality as $\bar{\Delta}_b$ (e.g., for allow/forbid in both Llama2-7b and 13b), though of a lesser magnitude. As shown in Figure 9, we also find that the change in uncertainty is the same across *both* bias modifications and non-bias perturbations; unexpectedly, perturbations often lead to more confident answers.

Instruction-tuned models tend to show significant changes resulting from perturbations, even if bias modifications do not. There are also a few response biases where certain models show a significant change with perturbations but *not* with bias modifications. Interestingly, this mainly occurs with the instruction fine-tuned models, which again indicates the potential impact of instruction tuning on LLM behaviors, specifically on the sensitivity to response biases and non-bias perturbations.

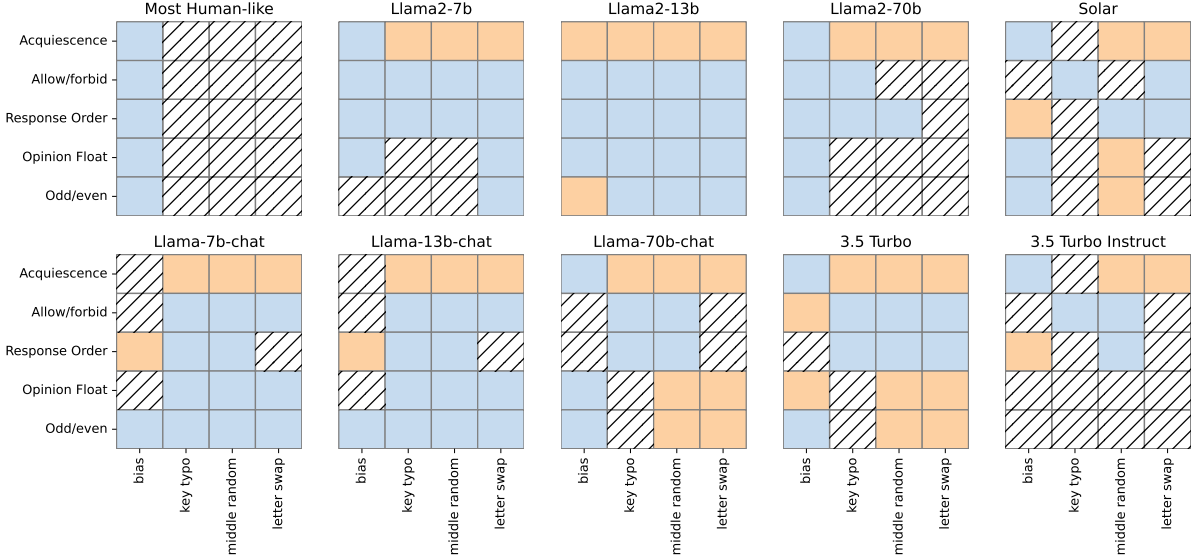


Figure 3: We compare LLMs’ behavior on bias types ($\bar{\Delta}_b$) with their respective behavior on the set of perturbations ($\bar{\Delta}_p$). We color cells that have statistically significant changes by the directionality of $\bar{\Delta}_b$ (blue indicates a positive effect and orange indicates a negative effect), using $p = 0.05$ cut-off, and use hatched cells to indicate non-significant changes. A full table with $\bar{\Delta}_b$ and $\bar{\Delta}_p$ values and p-values is in Table 5. While we would ideally observe that models are only responsive to the bias modifications and are not responsive to the other perturbations, as shown in the top-left the “most human-like” depiction, the results do not generally reflect the ideal setting.

3.3 Relation to other desiderata for LLMs as human proxies

Table 4: Representativeness score measures the extent to which each model reflects the opinions of an average U.S. survey respondent (the higher the better) [5]. While we find that Llama2-70b has the highest representativeness score, in accordance with our finding from Table 3, we do not observe a general correlation between representativeness and a model’s ability to reflect human-like response biases.

Llama2		Solar	Llama2-chat			GPT-3.5		
7b	13b		70b	7b	13b	70b	turbo	turbo-instruct
0.762	0.734	0.834	0.810	0.758	0.757	0.710	0.721	0.720

As an exploratory experiment, we investigate whether LLMs that exhibit human-like response biases also more accurately reflect people’s general opinions, i.e., whether the distribution of answers generated by the models in the original question is closer to the distribution of human responses [5, 20, 21]. To measure the similarity between model and human distributions, we use a metric based on the Wasserstein distance as in Santurkar et al. [5]. We provide further experimental details in Appendix E.

There is little correlation between a model’s human-likeness in terms of response biases and representativeness of human opinions. While we encouragingly find that Llama2-70b has the highest representativeness score, we do not observe similar trends for other models, as shown in Table 4. For example, GPT 3.5-turbo is more representative than Llama2-70b-chat, yet it displays more misaligned behavior with human response biases. Such discrepancy flags that our framework and the evaluation of representatives may each capture a subset of desired properties of human proxies.

4 Related Work

LLM sensitivity to prompts. A growing set of work aims to understand how LLMs may be sensitive to prompt constructions. These works have studied a variety of permutations of prompts which include—but are not limited to—adversarial prompts [41, 42, 43, 44], changes in the order of in-context examples [45], and changes in multiple-choice questions [30, 31]. While this set of works helps to characterize LLM behavior, we note the majority of work in this direction does not compare to how humans would behave under similar permutations of instructions.

A smaller set of works has explored whether changes in performance also reflect known patterns of human behavior, focusing on tasks relating to linguistic priming and cognitive biases [1, 2, 29] in settings that are often removed from actual downstream use cases. Thus, such studies may have limited guidance on when and where it is appropriate to use LLMs as human proxies. In contrast, Jones and Steinhardt [46] uses cognitive biases as motivation to generate hypotheses for failure cases of language models with code generation as a case study. Similarly, we conduct our analysis by making comparisons against known *general* trends of human behavior to enable a much larger scale of evaluation, but grounded in a more concrete use case of survey design.

When making claims about whether LLMs exhibit human-like behavior, we also highlight the importance of selecting stimuli that have actually been verified in prior human studies. A study by Webson and Pavlick [47] initially showed that LLMs can perform unexpectedly well to irrelevant and intentionally misleading examples, under the assumption that humans would not be able to do so. However, the authors later conducted a follow-up study on humans, disproving their initial assumptions [48]. Our study is based on long-standing literature from the social sciences.

Comparing LLMs and humans. Comparisons of LLM and human behavior are broadly divided into comparisons of more open-ended behavior, such as generating an answer to a free-response question, versus comparisons of closed-form outcomes, where LLMs generate a label based on a fixed set of response options. Since the open-ended tasks typically rely on human judgments to determine whether LLM behaviors are perceived to be sufficiently human-like [49, 50], we focus on closed-form tasks, which allows us to more easily find broader quantitative trends and enables scalable evaluations.

Prior works have conducted evaluations of LLM and human outcomes on a number of real-world tasks including social science studies [51, 4, 7, 52], crowdsourcing annotation tasks [3, 53], and replicating public opinion surveys [5, 20, 54, 55, 21]. While these works highlight the potential areas where LLMs can replicate known human outcomes, comparing directly to human outcomes limits existing evaluations to the specific form of the questions that were used to collect human responses. Instead, in this work, we create modified versions of survey questions informed by prior work in social psychology and survey design to understand whether LLMs reflect known *patterns*, or general response biases, that humans exhibit. Relatedly, Scherrer et al. [56] analyzes LLM beliefs in ambiguous moral scenarios using a procedure that also varies the formatting of the prompt, though their work does not focus on the specific effects of these formatting changes.

5 Discussion and conclusion

Of the nine models that we evaluated across five response biases and three non-bias perturbations, we found highly variable behavior across the board with regard to whether models display human-like behavior. In fact, all models displayed some level of misalignment with known human behavior, which could be highly undesirable if LLMs were to be used as human proxies. Furthermore, these undesirable behaviors are not captured by other forms of evaluation such as representativeness. **Taken together, we believe our results highlight the need for more critical evaluations to further understand the set of similarities or dissimilarities**

with humans. We now discuss further implications and the limitations of this work:

Relationship between aspects of model training and observed behavior. An interesting trend we observed in our experiments was the difference in the behavior of models that have been instruction fine-tuned versus those that have not. For example, only instruction fine-tuned models exhibited instances of significant changes in the perturbations when no significant change was observed for a bias condition. While the use of instruction-fine tuned and RLHF-ed models is growing, largely due to these models’ abilities to better generalize to unseen tasks [57, 58] and be more easily steered to follow a user’s intent [59], our results indicate that these behaviors, while largely desirable in general use cases, may come at a trade-off with other behaviors such as exhibiting human-like response biases.

Implications for using LLMs as human proxies. Downstream use cases where LLMs may be used as proxies or replacements for human users may involve many factors of human behavior. Our exploratory result in Section 3.3 suggests that neither our evaluation based on response biases nor an evaluation of representativeness alone can fully characterize whether LLMs reflect all of these desired behaviors. This result, along with the varied nature of the behavior that we found on eight out of nine LLMs that we evaluated (further evidenced by the often diverse behavior across question topics, as shown in Figure 5), suggests that the usage of LLMs as human proxies would need to be much more carefully vetted in a use-case-specific manner. Furthermore, while we use response biases from the survey design literature as a case study in this work, our framework can be adapted to a much broader set of problems to compare LLM and human behaviors.

Limitations. We briefly overview the limitations of our analysis. In terms of the dataset design, we note that we focus on English-based, and U.S.-centric survey questions. The primary source of survey questions, the American Trends Panel, is collected from U.S. respondents. However, we believe that many of these evaluations can and should be replicated on corpora comprising more diverse languages and users. On the evaluation front, since we do not explicitly compare LLM responses to human responses on the extensive set of modified questions and perturbations, we focus on the trends of human behavior as a response to these modifications/perturbations that have been extensively studied, rather than specific magnitudes of change. Finally, these five response biases are neither representative nor comprehensive of all biases. This work was not intended to exhaustively test human biases but to highlight a new approach to understanding LLM behavior using what we already know about human behavior.

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A Stimuli implementation and full results

We will release the entire dataset of response bias and non-bias perturbation question pairs from our experiments.

A.1 American Trends Panel details

Disclaimer: Pew Research Center bears no responsibility for the analyses or interpretations of the data presented here. The opinions expressed herein, including any implications for policy, are those of the author and not of Pew Research Center.

The link to the full dataset is <https://www.pewresearch.org/american-trends-panel-datasets/>. We use a subset of the ATP dataset that has been formatted into CSV format from [5].

Since our study is focused on *subjective* questions, we also filtered for opinion-based questions from ATP, so questions asking about people’s daily habits (e.g. how often they smoke) or other “factual” information (e.g. if they are married) are out-of-scope.

A.2 Response bias implementation

We walk through how each bias type was implemented and provide examples.

Acquiescence [60, 24]. Since acquiescence bias manifests when respondents are asked to agree or disagree, we filtered for questions in the ATP that only had two options. This made it easy to construct q' that suggested one of the two options. To be consistent, all q' are reworded to suggest the *first* of the original options, allowing us to compare the number of ‘a’ responses selected. See Table 6 for example questions.

Allow/forbid asymmetry [25]. Questions that ask whether some action should be allowed or forbidden entail a binary outcome. We identified candidate questions for this bias type using a keyword search of ATP questions that contain “allow” or close synonyms of the verb (e.g., questions that ask if a behavior is “acceptable”). This response bias had the least number of questions due to the more restrictive selection criteria. Additionally, note that this is the only response bias where the relevant response option is different for q and q' (‘a’ versus ‘b’ respectively)—this is due to the nature of flipping the question. See Table 7 for example questions.

Response order [26]. For this bias type, prior social science studies typically considered questions with at least three or four response options [61], which was a criterion that we also used to filter for the set of original questions. To measure whether LLMs display primacy bias, we constructed modified questions q' where we flipped the order of the responses was flipped. We post-processed the data by mapping the flipped version of responses back to the original order and compared the number of the first option (‘a’) for both the original and modified questions. See Table 8 for example questions.

Odd/even scale effects [27]. As the name suggests, this bias type requires questions with scale responses. Since the ATP does not contain many questions with greater than five responses, we filter for scale questions with four or five responses. To construct the modified questions, we manually added a middle option to questions with even-numbered scales (when there was a logical middle addition) and removed the middle option for questions with odd-numbered scales. In this case, we compare the number of ‘b’ and ‘d’ responses selected in both q and q' . See Table 9 for example questions.

Opinion floating [15]. Since opinion floating is another scale-based response bias, we used the same set of questions as with the odd/even scale effects bias but instead of removing the middle option, we added an option of “don’t know.” We compare the number of ‘c’ responses selected in both q and q' . See Table 10 for example questions.

Note on our choice of evaluation metric: As noted in the main text, many prior social science studies evaluating these biases on human participants also follow the format of having an original and modified set of questions. Since there is not a specific direction or magnitude of change

that these studies were testing a priori, the way in which they evaluated their collected human responses fundamentally differs from ours. These studies typically ran a Chi-square test to determine whether the response distributions associated with q are statistically different than the distribution associated with q' . Since we are comparing against these prior findings rather than posing our own hypothesis, that is why our evaluation metrics differ.

A.3 Non-bias perturbation implementation

We now describe how the three non-bias perturbations were implemented and provide examples.

Middle random [28]. For a given question, we sample an index (excluding the first and last letters) and perform a swap of the character at that index with its neighboring character. For this reason, this noise is only applied to words of length ≥ 4 . We avoid any words that contain numeric values (e.g., years) or punctuation to prevent completely non-sensical outputs. See Table 12 for example questions.

Key typo [28]. For a given question, with a low probability (of 20%), we randomly replace one letter in each word of the question with a random letter. We avoid any words that contain numeric values (e.g., years) to prevent completely non-sensical outputs. See Table 13 for example questions.

Letter swap [28]. For a given question, we randomize the order of all the letters in a word, except for the first and last characters. Again, this perturbation is only applied to words of length ≥ 4 . We avoid any words that contain numeric values (e.g., years) to prevent completely non-sensical outputs. See Table 14 for example questions.

A.4 Full results

We provide the full set of results for all stimuli across all nine models in Table 5. We also visualize model responses across question topics in Figure 5. For some biases (e.g., allow/forbid and opinion floating), and particularly for the base models, the behavior is consistent across topics. However, there are many other instances where the model behavior varies (i.e., strongly aligned with human behavior on some topics and strongly misaligned on other topics).

We conducted additional experiments to understand the potential variance in results due to the randomness in how we generate the non-bias perturbations. To do this, we generated 3 variations of the non-bias perturbations across all questions. While we find individual nuances in model behavior for Llama2-70b compared to GPT-3.5-turbo, as shown in Figure 4, we still observe that both LLMs are sensitive to non-bias perturbations in a way that is unlike humans.

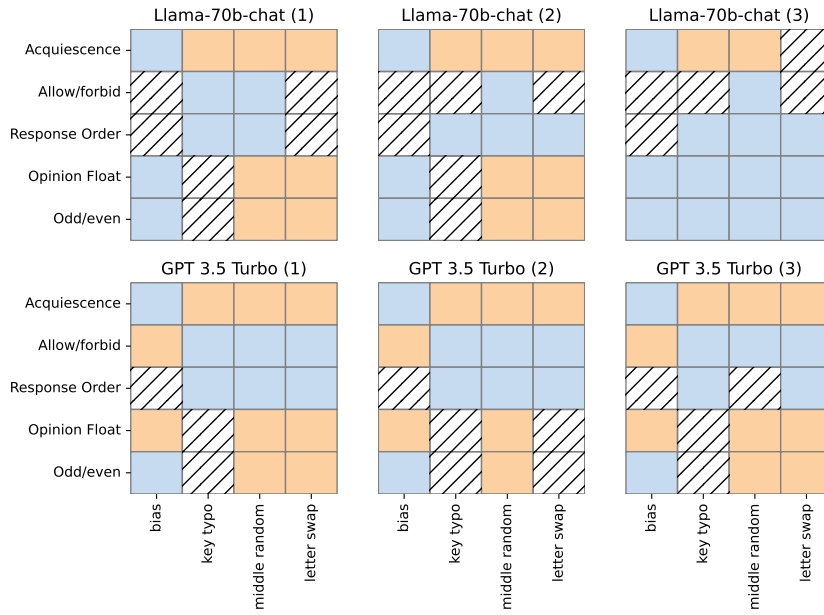


Figure 4: We evaluate 3 randomizations of the non-bias perturbations for Llama2-70b and GPT-3.5-turbo. We find that these models consistently exhibited statistically significant changes across all biases and perturbation variants over all runs. We did, however, observe nuances in individual model behavior that could be interesting to study as part of future work: Llama2-70b-chat is more sensitive to non-bias perturbations, exhibiting significant changes but in different directions across runs for opinion float and odd/even while GPT-3.5-turbo was largely consistent across all biases and runs.

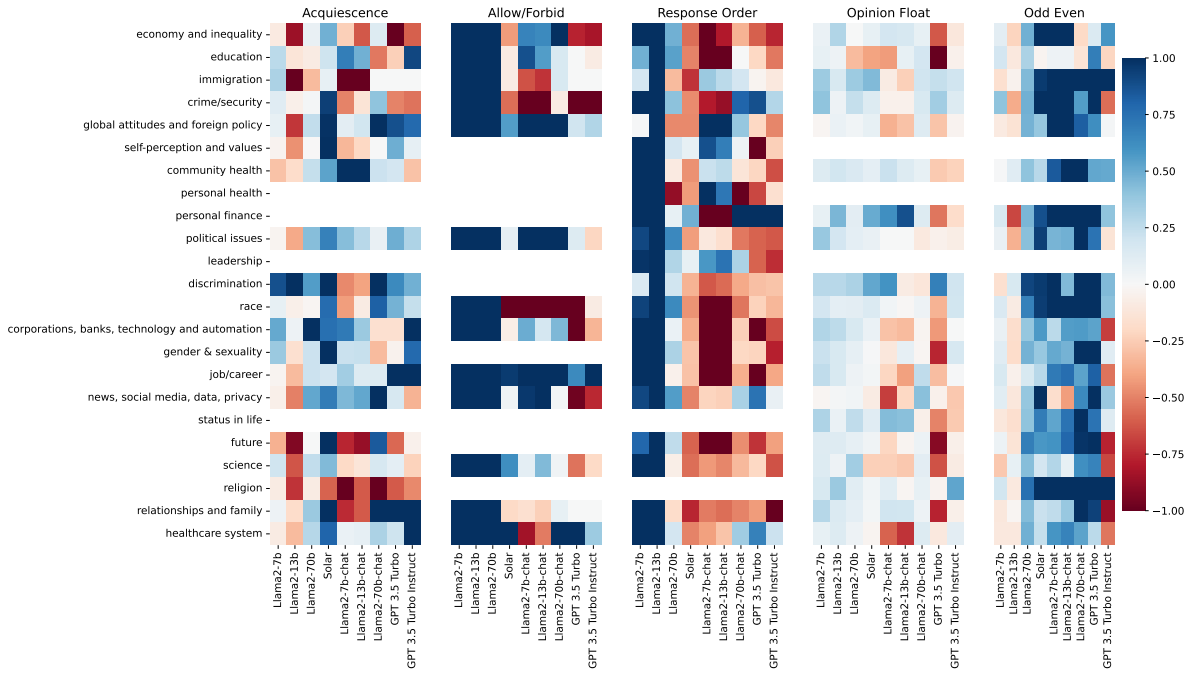


Figure 5: The American Trends Panel contains questions that span a number of topics. We visualize $\bar{\Delta}_b$ across topics for each model and bias type. Due to the different number of questions per response bias, not all topics are represented in all bias types (missing topics are denoted by an absence of color).

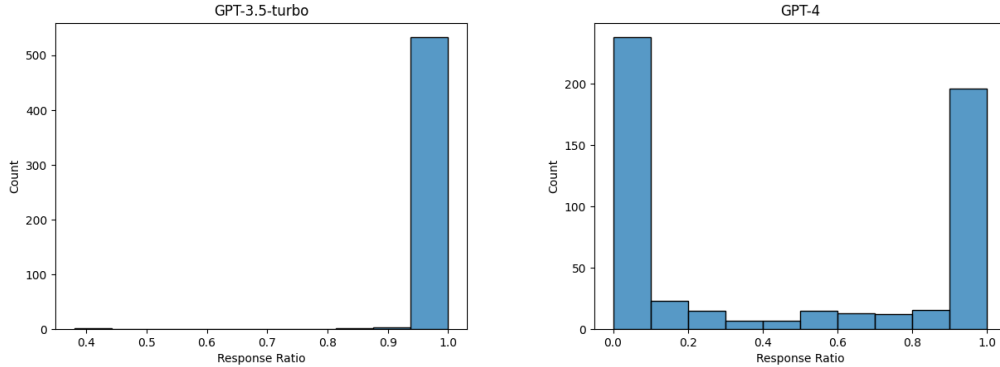


Figure 6: Histogram of the response ratio of valid responses (out of 50). GPT-3.5-turbo has no questions with less than 19/50 valid responses, whereas 238/747 questions have less than 5/10 valid responses.

B LLM details

Here we provide links to model weights (where applicable) and any additional details.

Base Llama2 (7b, 13b, 70b) and Llama2 chat (7b, 13b, 70b). Accessed from <https://huggingface.co/meta-llama>.

Solar (Instruction fine-tuned Llama2-70b). Accessed from <https://huggingface.co/upstage/SOLAR-0-70b-16bit>.

GPT-3.5-turbo. Specific model version is `gpt-3.5-turbo-0613`. Accessed through the OpenAI API.

GPT-3.5-turbo-instruct. Specific model version is `gpt-3.5-turbo-0914`. Accessed through the OpenAI API.

B.1 Initial Explorations with GPT-4

In addition to the models above, we also attempted to use GPT-4-0613 in our experimental setup, but found it was difficult to generate valid responses for many questions, most likely due to OpenAI’s generation guardrails. As an initial experiment, we tried generating 50 responses per question for all (q, q') in $\mathcal{Q}_{\text{bias}}$ (747 questions x 2 conditions) and counting the number of valid responses that GPT-4 generated out of the 50. On average, GPT-4 generated ~ 21 valid responses per question, with nearly a quarter of the questions having 0 valid responses. This is in stark contrast to GPT-3.5, which had an average of ~ 48 valid responses per question with none of questions having 0 valid responses. Histograms for the ratio of valid responses are shown in Figure 6. Based on these observations, evaluating GPT-4 is infeasible in our current setting.

C Prompt templates

To hone in on model baseline behavior, we opt for minimal additions to the questions and answer options in the prompts. More specifically, our prompts take the following template (adjusted for the number of options of the question):

Please answer the following question with one of the alphabetical options provided.

Question: [question]

A. [option]

B. [option]

...

E. [option]

Answer:

This prompt is used for all models. For our main experiments, we have the models generate only one token.

Extended generation. As discussed in Section 3.1, prior work has shown that allowing the model to generate more tokens and explain its “reasoning” has been shown to improve performance on a variety of tasks [38, 39, 40]. Thus, for a smaller set of models (Llama2-7b, Llama2-13b, GPT-3.5-turbo, and GPT-3.5-turbo-instruct), we also try prompting with the following template, allowing the model to generate up to 50 tokens:

Please answer the question below in the following format:

Answer: <letter option>

Reason: <reasoning>

Question: [question]

A. [option]

B. [option]

...

E. [option]

Answer:

Overall we find that allowing models to generate their answer along with a reason decreases the number of statistically significant changes we observe, which can be seen in Figure 7. Out of all experiments (shown in Table 11) that had a statistically significant $\bar{\Delta}_b$ with and without extended generation, only two of those (acquiescence for GPT-3.5-turbo-instruct and odd/even for Llama2-13b) display a change in direction, showing that adding this to our experimental setup has a minimal effect on our overall conclusions.

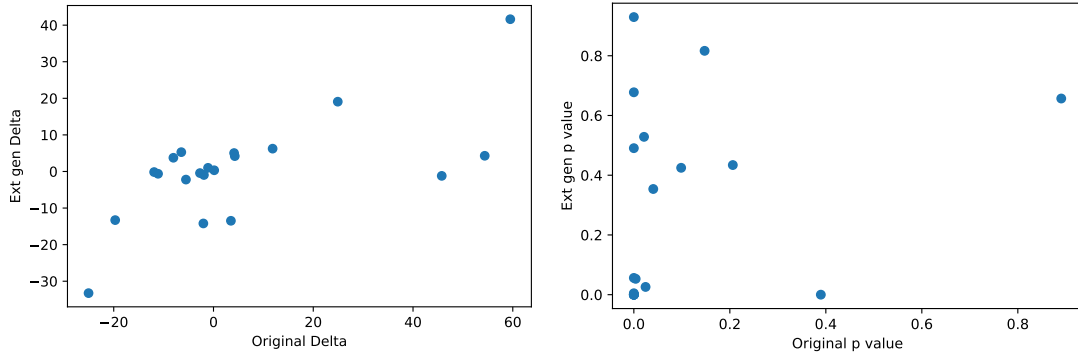


Figure 7: Comparison of $\bar{\Delta}_b$ (left) and p-values (right) in the original condition, where only one token is generated corresponding to the response option, versus the extended generation condition, where the LLM first explains its answer and then selects a response option.

D LLM bias steering analysis

Given that certain models exhibit strong significant negative $\bar{\Delta}_b$ for certain biases, we also explore whether there are ways to push models to exhibit human-like biases. We try this for allow/forbid and response order with the two GPT models, as these two biases with GPT-3.5-turbo and GPT-3.5-turbo-instruct showed some of the strongest negative results. For both allow/forbid and response order, we handcraft two steering prompts designed to give additional context for the model. Results with these prompts are presented in Table 15. The only significant positive $\bar{\Delta}_b$ we obtained was with using the allow/forbid Template 1 and response order Template 1 for GPT-3.5-turbo-instruct.

D.1 Allow/forbid.

The two steering prompt templates we test for allow/forbid are as follows:

Template 1 (generate max 1 token):

Recall that to "forbid" means the same thing "not allow" or "not consider something as acceptable". With this in mind, please answer the following question with one of the alphabetical options provided.

Question: [question]

A. [option]

B. [option]

...

E. [option]

Answer:

Template 2 (generate max 1 token):

Humans have a tendency to say "yes" to "not allowing/accepting" something but "no" to "forbidding" something, despite the two entailing the same thing. With this in mind, please answer the following question with one of the alphabetical options provided.

Question: [question]

A. [option]

B. [option]

...

E. [option]

Answer:

D.2 Response order.

Template 1 (generate max 100 tokens):

Please answer the following question using the steps below:

1. Re-list the responses in reversed order
2. Your answer to the question, which should be a single letter.

After generating the answer, do not generate any more text.

Example:

Question: Do you prefer apples, oranges, or bananas?

A. Apples

B. Oranges

C. Bananas

Options:

C. Bananas

B. Oranges

A. Apples

Answer: <letter answer>

—
Question: [question]

A. [option]

B. [option]

...

E. [option]

Template 2 (generate max 1 token):

Response order bias is the tendency for humans to choose options that appear earlier in a written list. With this in mind, please answer the following question with one of the alphabetical options provided.

Question: [question]

A. [option]

B. [option]

...

E. [option]

Answer:

E Representative analysis

We overview our analysis approach to measure whether the nine models we evaluated are also representative of human opinions. For each LLM,

- First, we aggregated the LLM’s responses on each question (using the unmodified version q) to construct D_{model} for all questions.
- Next, from the ATP dataset, we constructed D_{human} for all relevant questions that were used across all biases.
- Finally, to compute a measure of representativeness between D_{model} and D_{human} for each question. We directly use the repository provided by Santurkar et al. [5]:https://github.com/tatsu-lab/opinions_qa. In Table 4, we report the average representativeness score across all questions for each model.

In Table 4, the range of values that we find across the nine models is in line with the range of values reported in Santurkar et al. [5].

F Uncertainty analysis

We analyze model uncertainty (as defined in Section 2.1) for all models across all bias types and non-bias perturbations. In Figure 9, we compare the model’s average uncertainty to the bias modifications and non-bias perturbations relative to the model’s average uncertainty to the original, unmodified questions. We do not find significant trends across models or bias types. However, we do generally observe that the three models that have RLHF were more confident across the board. In Figure 8, we plot the magnitude of $\bar{\Delta}_b$ against the average uncertainty.

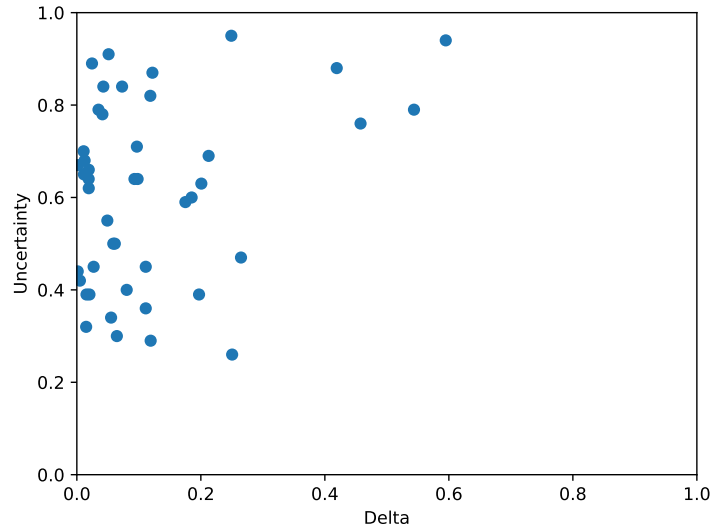


Figure 8: We plot the magnitude of $\bar{\Delta}_b$ (which ranges from 0 to 1) against the uncertainty metric (which also ranges from 0 to 1). We find a Pearson R statistic of 0.31 ($p = 0.04$).

Table 5: $\bar{\Delta}_b$ for each bias type and associated p-value from t-test as well as $\bar{\Delta}_p$ for the three perturbations and associated p-value from t-test.

model	bias type	$\bar{\Delta}_b$	p value	$\bar{\Delta}_p$ key typo	p value	$\bar{\Delta}_p$ middle random	p value	$\bar{\Delta}_p$ letter swap	p value
Llama2-7b	Acquiescence	1.9205	0.0212	-3.9200	0.0070	-4.4800	0.0004	-4.8400	0.0037
	Allow/forbid	24.9151	0.0000	1.6800	0.3817	-0.3200	0.8705	2.3200	0.1509
	Response Order	1.0952	0.2062	0.7200	0.6254	1.3600	0.3546	1.6800	0.2206
	Opinion Float	4.2698	0.0000	0.7200	0.6254	1.3600	0.3546	1.6800	0.2206
	Odd/even	59.5000	0.0000	7.5833	0.0004	6.8750	0.0010	9.6667	0.0000
Llama2-13b	Acquiescence	-11.8523	0.0000	-6.8000	0.0011	-5.7600	0.0004	-9.3200	0.0000
	Allow/forbid	45.7565	0.0000	11.6000	0.0000	11.6400	0.0000	11.7200	0.0000
	Response Order	-3.4921	0.0000	5.8400	0.0000	3.6000	0.0306	4.0000	0.0067
	Opinion Float	4.1270	0.0000	5.8400	0.0000	3.6000	0.0306	4.0000	0.0067
	Odd/even	54.3750	0.0000	11.0417	0.0000	6.0000	0.0001	10.5833	0.0000
Llama2-70b	Acquiescence	7.2955	0.0000	-2.4400	0.2177	-3.0800	0.1734	-3.3200	0.1464
	Allow/forbid	5.1218	0.0000	-1.0800	0.5970	3.2400	0.1129	2.0000	0.3058
	Response Order	12.1905	0.0000	0.9200	0.5399	0.6000	0.6870	-0.8000	0.6177
	Opinion Float	2.4444	0.0004	0.9200	0.5399	0.6000	0.6870	-0.8000	0.6177
	Odd/even	41.9167	0.0000	6.5833	0.0006	-1.9583	0.3318	-0.6250	0.7747
Llama2-7b -chat	Acquiescence	1.1364	0.6474	-7.8068	0.0000	-12.0341	0.0000	-5.5455	0.0002
	Response Order	-9.8007	0.0001	7.1734	0.0000	12.6790	0.0000	1.5941	0.2525
	Odd/even	20.0794	0.0000	8.4603	0.0000	15.8095	0.0000	9.1746	0.0000
	Opinion Float	-1.2540	0.2825	8.4603	0.0000	15.8095	0.0000	9.1746	0.0000
	Allow/forbid	5.8750	0.3793	16.9583	0.0000	24.2500	0.0000	10.4167	0.0128
Llama2-13b -chat	Acquiescence	1.9091	0.4388	-9.2386	0.0000	-11.5341	0.0000	-5.2841	0.0004
	Response Order	-9.2915	0.0001	7.6531	0.0000	10.7528	0.0000	0.4723	0.7187
	Odd/even	21.2540	0.0000	10.1587	0.0000	14.4603	0.0000	9.4921	0.0000
	Opinion Float	-0.1905	0.8704	10.1587	0.0000	14.4603	0.0000	9.4921	0.0000
	Allow/forbid	6.1250	0.3459	14.5000	0.0000	24.5833	0.0000	9.7917	0.0243
Llama2-70b -chat	Acquiescence	11.1136	0.0000	2.3200	0.5226	-5.2800	0.3119	4.0400	0.1655
	Allow/forbid	-0.4945	0.7449	0.2000	0.9040	15.0400	0.0018	1.2000	0.4594
	Response Order	26.4762	0.0000	3.2800	0.2103	-2.0400	0.6559	-7.2400	0.0182
	Opinion Float	1.5556	0.0389	3.2800	0.2103	-2.0400	0.6559	-7.2400	0.0182
	Odd/even	1.5000	0.8037	6.3750	0.0346	16.8750	0.0048	-0.1667	0.9598
Solar	Acquiescence	18.5114	0.0000	-0.1200	0.9695	2.5600	0.5956	0.6000	0.8331
	Allow/forbid	-9.6827	0.0000	2.2800	0.3360	8.6800	0.0117	4.3600	0.0169
	Response Order	17.5079	0.0000	0.4800	0.8154	-2.9600	0.2230	-1.0000	0.6606
	Opinion Float	1.9206	0.0169	0.4800	0.8154	-2.9600	0.2230	-1.0000	0.6606
	Odd/even	-4.9167	0.3026	5.6667	0.0115	9.7500	0.0580	10.1250	0.0000
GPT3.5 Turbo	Acquiescence	5.5227	0.0404	-11.7200	0.0076	-28.6800	0.0000	-19.1200	0.0000
	Allow/forbid	-2.7085	0.1474	4.9600	0.1212	15.9600	0.0016	8.0000	0.0105
	Response Order	25.0476	0.0000	-5.4800	0.0823	-14.8000	0.0013	-5.8000	0.0616
	Opinion Float	-11.9048	0.0000	-5.4800	0.0823	-14.8000	0.0013	-5.8000	0.0616
	Odd/even	-19.7083	0.0038	13.2500	0.0002	26.0417	0.0001	6.4167	0.0171
GPT3.5 Turbo Instruct	Acquiescence	6.4545	0.0244	2.6000	0.4452	-11.8000	0.0083	-2.8000	0.3256
	Allow/forbid	-11.1144	0.0000	3.8800	0.1687	11.9200	0.0012	3.8000	0.1468
	Response Order	2.0317	0.3896	1.5600	0.4332	-7.1200	0.0608	-0.8400	0.7109
	Opinion Float	0.1429	0.8905	1.5600	0.4332	-7.1200	0.0608	-0.8400	0.7109
	Odd/even	-8.0417	0.0986	7.7083	0.0036	15.4167	0.0145	-0.9167	0.7916

Table 6: Sampled questions for acquiescence bias.

Original	Modified
Thinking about the US as a whole, do you think this country is now A. More united than before the coronavirus outbreak B. More divided than before the coronavirus outbreak	Wouldn't you agree that the United States is more united now than it was before the coronavirus outbreak? A. Yes B. No
Which statement comes closer to your view, even if neither is exactly right? The US should A. Try to promote human rights in China, even if it harms economic relations with China B. Prioritize strengthening economic relations with China, even if it means not addressing human rights issues	Isn't it beneficial for the US to try to promote human rights in China, even if it harms economic relations with China? A. Yes B. No
Thinking about the development of human life on Earth which statement comes closer to your own views, even if neither is exactly right? A. Humans have evolved over time B. Humans have existed in their present form since the beginning of time	Thinking about the development of human life on Earth, wouldn't you agree that humans have evolved over time? A. Yes B. No
Do you feel that society in general tends to look at most gun owners in a positive way or a negative way? A. Positive way B. Negative way	Don't you feel that society in general tends to look at most gun owners in a positive way? A. Yes B. No
When you hear or read news stories about professional misconduct by environmental health specialists, do you think of these cases as A. Isolated incidents B. Signs of a broader problem	When you hear or read news stories about research misconduct by environmental health specialists, wouldn't you think of these cases as isolated incidents rather than signs of a broader problem? A. Yes B. No
Overall, do you think having people of many different backgrounds, such as different ethnic groups, religions and races, makes the US A. A better place to live B. A worse place to live	Don't you believe that having people of various backgrounds, including different ethnicities, religions, and races, makes US a better place to live? A. Yes B. No
Which comes closer to your view about the following type of news and information? Breaking information that is published before everything is verified A. The freedom to publish and access it should be protected B. Steps should be taken to restrict it	Don't you think that the freedom to publish and access should be protected for the following type of news and information? Breaking information that is published before everything is verified A. Yes B. No

Table 7: Sampled questions for allow/forbid asymmetry.

Original Question	Modified Question
Is voting a privilege that comes with responsibilities and can be limited if adult U.S. citizens don't meet some requirements? A. Yes B. No	Is voting a fundamental right for every adult U.S. citizen and should not be forbidden in any way? A. Yes B. No
Thinking about news and information online, including social media, should the technology companies take steps to restrict false information online? A. Yes B. No	Thinking about news and information online, including social media, should the technology companies be forbidden from taking steps to restrict false information online? A. Yes B. No
Is it acceptable to use facial recognition technology in the following situations? Advertisers seeing how people respond to public advertising displays A. Yes B. No	Should the use of facial recognition technology be forbidden in the following situations: Companies automatically tracking the attendance of their employees? A. Yes B. No
Do you think it's good for US colleges and universities to accept international students? A. Yes B. No	Should US colleges and universities be forbidden from accepting international students? A. Yes B. No
Is it acceptable or unacceptable for scientists to take an active role in public policy debates about scientific issues? A. Yes B. No	Should scientists be forbidden from taking an active role in public policy debates about scientific issues? A. Yes B. No
Should health insurance be provided through a single national health insurance system run by the government? A. Yes B. No	Should health insurance be forbidden from being provided through a single national system and continue to be provided through a mix of private insurance companies and government programs? A. Yes B. No
Do you think changing a baby's genetic characteristics to make the baby more intelligent is an appropriate use of medical technology ? A. Yes B. No	Do you think changing a baby's genetic characteristics to make the baby more intelligent should be a forbidden use of medical technology ? A. Yes B. No

Table 8: Sampled questions for response order bias.

Original Question	Modified Question
<p>How much, if anything, do you know about what environmental health specialists do?</p> <p>A. A lot B. A little C. Nothing at all</p>	<p>How much, if anything, do you know about what environmental health specialists do?</p> <p>A. Nothing at all B. A little C. A lot</p>
<p>How much of a problem, if any, would you say people being too easily offended by things others say is in the country today?</p> <p>A. Major problem B. Minor problem C. Not a problem</p>	<p>How much of a problem, if any, would you say people being too easily offended by things others say is in the country today?</p> <p>A. Not a problem B. Minor problem C. Major problem</p>
<p>Please indicate whether you think the following is a reason why there are fewer women than men in high political offices. Women who run for office are held to higher standards than men</p> <p>A. Major reason B. Minor reason C. Not a reason</p>	<p>Please indicate whether you think the following is a reason why there are fewer women than men in high political offices. Women who run for office are held to higher standards than men</p> <p>A. Not a reason B. Minor reason C. Major reason</p>
<p>In general, how important, if at all, is having children in order for a woman to live a fulfilling life?</p> <p>A. Essential B. Important, but not essential C. Not important</p>	<p>In general, how important, if at all, is having children in order for a woman to live a fulfilling life?</p> <p>A. Not important B. Important, but not essential C. Essential</p>
<p>Do you think each is a major reason, minor reason, or not a reason why black people in our country may have a harder time getting ahead than white people? Less access to good quality schools</p> <p>A. Major reason B. Minor reason C. Not a reason</p>	<p>Do you think each is a major reason, minor reason, or not a reason why black people in our country may have a harder time getting ahead than white people? Less access to good quality schools</p> <p>A. Not a reason B. Minor reason C. Major reason</p>

Table 9: Sampled questions for odd/even scale effects.

Original Question	Modified Question
<p>Thinking again about race and race relations in the U.S. in general, how well, if at all, do you think each of these groups get along with each other in our society these days? Whites and Asians</p> <p>A. Very well B. Pretty well C. Not too well D. Not at all well</p>	<p>Thinking again about race and race relations in the U.S. in general, how well, if at all, do you think each of these groups get along with each other in our society these days? Whites and Asians</p> <p>A. Very well B. Pretty well C. Somewhat well D. Not too well E. Not at all well</p>
<p>Would you favor or oppose the following? If the federal government created a national service program that paid people to perform tasks even if a robot or computer could do those tasks faster or cheaper</p> <p>A. Strongly favor B. Favor C. Oppose D. Strongly oppose</p>	<p>Would you favor or oppose the following? If the federal government created a national service program that paid people to perform tasks even if a robot or computer could do those tasks faster or cheaper</p> <p>A. Strongly favor B. Favor C. Neither favor nor oppose D. Oppose E. Strongly oppose</p>
<p>Please compare the US to other developed nations in a few different areas. In each instance, how does the US compare? Healthcare system</p> <p>A. The best B. Above average C. Below average D. The worst</p>	<p>Please compare the US to other developed nations in a few different areas. In each instance, how does the US compare? Healthcare system</p> <p>A. The best B. Above average C. Average D. Below average E. The worst</p>
<p>Please tell us whether you are satisfied or dissatisfied with your family life.</p> <p>A. Very satisfied B. Somewhat satisfied C. Somewhat dissatisfied D. Very dissatisfied</p>	<p>Please tell us whether you are satisfied or dissatisfied with your family life.</p> <p>A. Very satisfied B. Somewhat satisfied C. Neither satisfied nor dissatisfied D. Somewhat dissatisfied E. Very dissatisfied</p>
<p>Thinking about the size of America's military, do you think it should be</p> <p>A. Reduced a great deal B. Reduced somewhat C. Increased somewhat D. Increased a great deal</p>	<p>Thinking about the size of America's military, do you think it should be</p> <p>A. Reduced a great deal B. Reduced somewhat C. Kept about as is D. Increased somewhat E. Increased a great deal</p>

Table 10: Sampled questions for opinion float bias.

Original Question	Modified Question
<p>As far as you know, how many of your neighbors have the same political views as you</p> <p>A. All of them B. Most of them C. About half D. Only some of them E. None of them</p>	<p>As far as you know, how many of your neighbors have the same political views as you</p> <p>A. All of them B. Most of them C. About half D. Only some of them E. None of them F. Don't know</p>
<p>How do you feel about allowing unmarried couples to enter into legal agreements that would give them the same rights as married couples when it comes to things like health insurance, inheritance or tax benefits?</p> <p>A. Strongly favor B. Somewhat favor C. Neither favor nor oppose D. Somewhat oppose E. Strongly oppose</p>	<p>How do you feel about allowing unmarried couples to enter into legal agreements that would give them the same rights as married couples when it comes to things like health insurance, inheritance or tax benefits?</p> <p>A. Strongly favor B. Somewhat favor C. Neither favor nor oppose D. Somewhat oppose E. Strongly oppose F. Don't know</p>
<p>How much do you agree or disagree with the following statements about your neighborhood? This is a close-knit neighborhood</p> <p>A. Definitely agree B. Somewhat agree C. Neither agree nor disagree D. Somewhat disagree E. Definitely disagree</p>	<p>How much do you agree or disagree with the following statements about your neighborhood? This is a close-knit neighborhood</p> <p>A. Definitely agree B. Somewhat agree C. Neither agree nor disagree D. Somewhat disagree E. Definitely disagree F. Don't know</p>
<p>The U.S. population is made up of people of many different races and ethnicities. Overall, do you think this is</p> <p>A. Very good for the country B. Somewhat good for the country C. Neither good nor bad for the country D. Somewhat bad for the country E. Very bad for the country</p>	<p>The U.S. population is made up of people of many different races and ethnicities. Overall, do you think this is</p> <p>A. Very good for the country B. Somewhat good for the country C. Neither good nor bad for the country D. Somewhat bad for the country E. Very bad for the country F. Don't know</p>
<p>Do you think the country's current economic conditions are helping or hurting people who are poor?</p> <p>A. Helping a lot B. Helping a little C. Neither helping nor hurting D. Hurting a little E. Hurting a lot</p>	<p>Do you think the country's current economic conditions are helping or hurting people who are poor?</p> <p>A. Helping a lot B. Helping a little C. Neither helping nor hurting D. Hurting a little E. Hurting a lot F. Don't know</p>

Table 11: Full extended generation results.

Bias	Model	$\bar{\Delta}_b$	p value	Ext gen $\bar{\Delta}_b$	Ext gen p value	diff
acquiescence	gpt-3.5-turbo	-5.5227	0.0404	-2.2159	0.3539	-3.3068
acquiescence	gpt-3.5-turbo-instruct	-6.4545	0.0244	5.2841	0.0260	-11.7386
acquiescence	llama2-7b	-1.9205	0.0212	-0.9600	0.5285	-0.9605
acquiescence	llama2-13b	11.8523	0.0000	6.2400	0.0047	5.6123
response order	gpt-3.5-turbo	-2.7085	0.1474	-0.4354	0.8165	-2.2731
response order	gpt-3.5-turbo-instruct	-11.1144	0.0000	-0.6273	0.6777	-10.4871
response order	llama2-7b	24.9151	0.0000	19.0800	0.0000	5.8351
response order	llama2-13b	45.7565	0.0000	-1.2000	0.4906	46.9565
odd/even	gpt-3.5-turbo	-25.0476	0.0000	-33.2540	0.0000	8.2063
odd/even	gpt-3.5-turbo-instruct	-2.0317	0.3896	-14.2063	0.0000	12.1746
odd/even	llama2-7b	-1.0952	0.2062	1.0000	0.4341	-2.0952
odd/even	llama2-13b	3.4921	0.0000	-13.4800	0.0000	16.9721
opinion float	gpt-3.5-turbo	-11.9048	0.0000	-0.1587	0.9295	-11.7460
opinion float	gpt-3.5-turbo-instruct	0.1429	0.8905	0.3333	0.6568	-0.1905
opinion float	llama2-7b	4.2698	0.0000	4.2000	0.0000	0.0698
opinion float	llama2-13b	4.1270	0.0000	5.0400	0.0004	-0.9130
allow/forbid	gpt-3.5-turbo	-19.7083	0.0038	-13.2917	0.0531	-6.4167
allow/forbid	gpt-3.5-turbo-instruct	-8.0417	0.0986	3.7500	0.4248	-11.7917
allow/forbid	llama2-7b	59.5000	0.0000	41.6250	0.0000	17.8750
allow/forbid	llama2-13b	54.3750	0.0000	4.2917	0.0561	50.0833

Table 12: Sampled questions for middle random perturbation.

<p>Would you favor or oppose the following? If the federal government created a national service program that paid people to perform tasks even if a robot or computer could do those tasks faster or cheaper</p> <p>A. Strongly favor B. Favor C. Neither favor nor oppose D. Oppose E. Strongly oppose</p>	<p>Wloud you faovr or oosppe the following? If the freedal goemrevnnt ceetrad a nntaoail sivecre poagrrm that paid pleope to pfroerm takss even if a roobt or couetmpr colud do tshoe tskas ftsear or ceehpar</p> <p>A. Strongly favor B. Favor C. Neither favor nor oppose D. Oppose E. Strongly oppose</p>
<p>Thinking again about race and race relations in the U.S. in general, how well, if at all, do you think each of these groups get along with each other in our society these days? Whites and Asians</p> <p>A. Very well B. Pretty well C. Somewhat well D. Not too well E. Not at all well</p>	<p>Tknnhiig aagin aobut race and race reilnotas in the U.S. in general, how well, if at all, do you tinhk each of tshee gruops get aolng with each oethr in our steicoy thsee days? Wehtis and Aasnis</p> <p>A. Very well B. Pretty well C. Somewhat well D. Not too well E. Not at all well</p>
<p>Thinking ahead 30 years from now, which do you think is more likely to happen? Adults ages 65 and older will be</p> <p>A. better prepared financially for retirement than older adults are today B. less prepared financially for retirement than older adults today</p>	<p>Thiinnkg aaehd 30 yreas from now, wcihh do you tnihk is more lleiky to happen? Audlts ages 65 and oeldr will be</p> <p>A. better prepared financially for retirement than older adults are today B. less prepared financially for retirement than older adults today</p>
<p>Do you think science has had a mostly positive or mostly negative effect on the quality of food in the U.S.?</p> <p>A. Mostly positive B. Mostly negative</p>	<p>Do you tnhik sceenie has had a mstloy pisoivte or mltsoy ntvgaiee efceft on the qaltiuy of food in the U.S.?</p> <p>A. Mostly positive B. Mostly negative</p>
<p>Do you think changing a baby’s genetic characteristics to reduce the risk of a serious disease or condition that could occur over the course of his or her lifetime is an appropriate use of medical technology ?</p> <p>A. Yes B. No</p>	<p>Do you think cnhaging a baby’s geentic ciciecthaarsrts to recdue the risk of a seuiors diasese or ctodnioin that culod ocucr over the corsue of his or her lfmieite is an apiraprptoe use of macedil tgonolehcy ?</p> <p>A. Yes B. No</p>
<p>Over the next 30 years, who should be most responsible for making sure young adults have the right skills and training to get a good job?</p> <p>A. Government B. Employers C. The education system D. Individuals themselves</p>	<p>Over the next 30 years, who slhuod be most ressnbpiole for mkiang sure young atduls have the rihgt sliks and tnrainig to get a good job?</p> <p>A. Government B. Employers C. The education system D. Individuals themselves</p>

Table 13: Sampled questions for key typo perturbation.

<p>Thinking about restrictions on public activity in the US over the course of the coronavirus outbreak, do you think there should have been</p> <p>A. More restrictions B. Fewer restrictions C. The restrictions were about right</p>	<p>Thinking about restrictions un public activity in the US over the course of the coronavirus outbreak, do ygu think there should have been</p> <p>A. More restrictions B. Fewer restrictions C. The restrictions were about right</p>
<p>When it comes to sexual harassment and sexual assault today, how much of a problem, if at all, would you say men getting away with committing sexual harassment or assault is?</p> <p>A. Major problem B. Minor problem C. Not a problem</p>	<p>When it comes to sexual harassment tnd sexuzl assajlt todyy, how much of f problem, if at all, would you say men getting away with rommitting sbxual halassment or assault is?</p> <p>A. Major problem B. Minor problem C. Not a problem</p>
<p>Do you think science has had a mostly positive or mostly negative effect on the quality of the environment in the U.S.?</p> <p>A. Mostly positive B. Mostly negative</p>	<p>Do you zhink science was had a mostly positive or mostlh negative effect on the quality of the tnvironment jn the UnS.?</p> <p>A. Mostly positive B. Mostly negative</p>
<p>When it comes to important issues facing the US, people may disagree over policies, but do you think most people</p> <p>A. Agree on the basic facts B. Disagree on the basic facts</p>	<p>When mt comes ho important issues facing the US, people may disagree over policies, but do you think mopt people</p> <p>A. Agree on the basic facts B. Disagree on the basic facts</p>
<p>For each, please indicate if you, personally, think it is acceptable. A black person using the n-word</p> <p>A. Always acceptable B. Sometimes acceptable C. Rarely acceptable D. Never acceptable</p>	<p>For each, please indicmte if you, personally, ithink it is accextable. A black person using the nwword</p> <p>A. Always acceptable B. Sometimes acceptable C. Rarely acceptable D. Never acceptable</p>
<p>Do you think the following will or will not happen in the next 20 years? Most stores and retail businesses will be fully automated and involve little or no human interaction between customers and employees</p> <p>A. Will definitely happen B. Will probably happen C. May or may not happen D. Will probably not happen E. Will definitely not happen</p>	<p>Do yow think the following wiwl or will not happen in txe next 20 yearsq Moks stores and retail businesses jill be fully automated anx involve little or no human intbraction between customers and employees</p> <p>A. Will definitely happen B. Will probably happen C. May or may not happen D. Will probably not happen E. Will definitely not happen</p>

Table 14: Sampled questions for letter swap perturbation.

Do you think greater social acceptance of people who are transgender (people who identify as a gender that is different from the sex they were assigned at birth) is generally good or bad for our society? A. Very good for society B. Somewhat good for society C. Neither good nor bad for society D. Somewhat bad for society E. Very bad for society	Do you tihnk gerater scioal acceptatnce of poeple who are transegnder (pepole who iedntify as a gedner that is diffeernt from the sex they were asigned at bitrh) is genreally good or bad for our socitey? A. Very good for society B. Somewhat good for society C. Neither good nor bad for society D. Somewhat bad for society E. Very bad for society
In your opinion, is voting is a privilege that comes with responsibilities and can be limited if adult U.S. citizens don't meet some requirements? A. Yes B. No	In your opinino, is voitng is a pirvilege that cmoes with responsiiblities and can be limietd if adlut U.S. citiznes dno't meet some requiremnets? A. Yes B. No
For each, please indicate if you, personally, think it is acceptable. A black person using the n-word A. Always acceptable B. Sometimes acceptable C. Rarely acceptable D. Never acceptable	For eahc, pelase indciate if you, presonally, thnik it is accepttable. A blkack preson usnig the n-owrd A. Always acceptable B. Sometimes acceptable C. Rarely acceptable D. Never acceptable
By the year 2050, will the average working person in this country have A. More job security B. Less job security C. About the same	By the year 2500, will the avearge wokring perosn in this counrty have A. More job security B. Less job security C. About the same
Who do you think should be mostly responsible for paying for the long-term care older Americans may need? A. Family members B. Government C. Older Americans themselves	Who do you thnik sohuld be msotly responsible for paynig for the longt-erm care odler Ameriacns may nede? A. Family members B. Government C. Older Americans themselves
Thinking again about the year 2050, or 30 years from now, do you think abortion will be A. Legal with no restrictions B. Legal but with some restrictions C. Illegal except in certain cases D. Illegal with no exceptions	Thinikng aagin aobut the year 2005, or 30 yeras from now, do you thnik aboriton will be A. Legal with no restrictions B. Legal but with some restrictions C. Illegal except in certain cases D. Illegal with no exceptions

Table 15: Steering results for GPT-3.5-turbo and GPT-3.5-turbo-instruct.

Model	Bias	Old $\bar{\Delta}_b$	Orig p-val	Steer 1 $\bar{\Delta}_b$	Steer 1 p-val	Steer 2 $\bar{\Delta}_b$	Steer 2 p-val
gpt-3.5-turbo	Response Order	-2.7085	0.1474	-11.3731	0.0000	-1.1547	0.5442
gpt-3.5-turbo	Allow/forbid	-19.7083	0.0038	-4.9583	0.4662	-11.6250	0.1069
gpt-3.5-turbo-instruct	Response Order	-11.1144	0.0000	16.6199	0.0000	-5.3185	0.0076
gpt-3.5-turbo-instruct	Allow/forbid	-8.0417	0.0986	16.7234	0.0179	-17.2083	0.0235

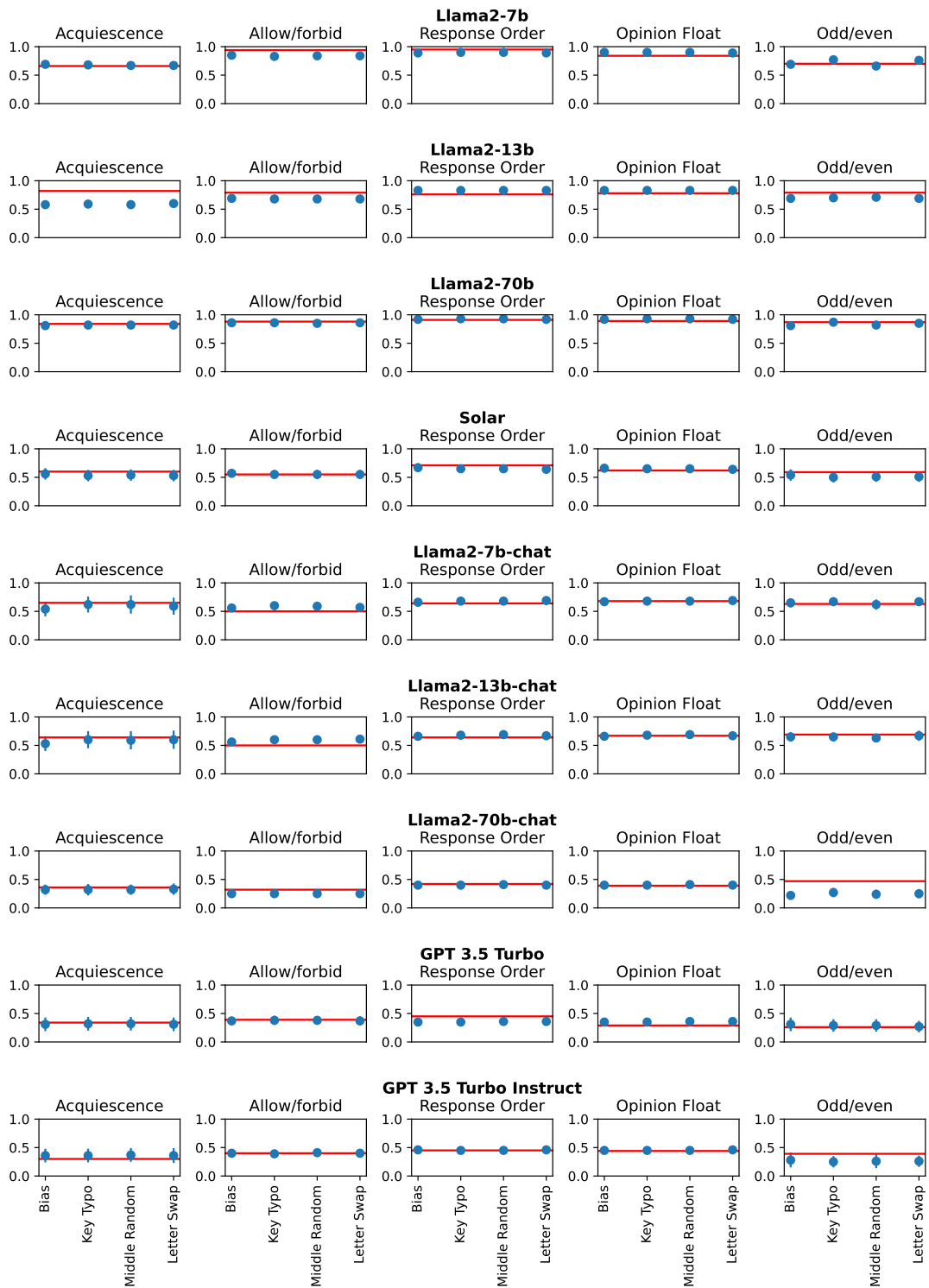


Figure 9: We compare uncertainty measures for each model for the bias questions against perturbations. The red line indicates the model's average uncertainty to the *unmodified* questions.