Just Put a Human in the Loop?
Investigating LLM-Assisted Annotation for Subjective Tasks

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Abstract

LLM use in annotation is becoming widespread, and given LLMs' overall promising performance and speed, putting humans in the loop to simply "review" LLM annotations can be tempting. In subjective tasks with multiple plausible answers, this can impact both evaluation of LLM performance, and analysis using these labels in a social science task downstream. In a pre-registered experiment with 350 unique annotators and 7,000 annotations across 4 conditions, 2 models, and 2 datasets, we find that presenting crowdworkers with LLM-generated annotation suggestions did not make them faster annotators, but did improve their self-reported confidence in the task. More importantly, annotators strongly took the LLM suggestions, significantly changing the label distribution compared to the baseline. We show that when these labels created with LLM assistance are used to evaluate LLM performance, reported model performance significantly increases. We show how changes in label distributions as a result of LLM assistance can affect conclusions drawn by analyzing even "human-approved" LLM-annotated datasets. We believe our work underlines the importance of understanding the impact of LLM-assisted annotation on subjective, qualitative tasks, on the creation of gold data for training and testing, and on the evaluation of NLP systems on subjective tasks.

1 Introduction

Large language models (LLMs) are showing impressive performance in many annotation tasks, including subjective tasks common in content moderation and text analysis in the social sciences. Evaluating human annotation of subjective tasks for comparison against LLM annotation performance, either for the task of end-to-end qualitative analysis or for the construction of ground truth for NLP tasks, is difficult in the absence of domain experts. Accordingly, hiring a large number of crowd annotators (often in service of creating a crowd decision) becomes attractive in the evaluation of NLP systems on social science tasks. However, managing and paying crowdworkers can be difficult, and crowdworkers often have varied performance.

A long line of research explores how AI suggestions can assist qualitative researchers (Jiang et al., 2021; Feuston and Brubaker, 2021; Overney et al., 2024). Labeling text according to a complex qualitative "codebook" is a repetitive, time-consuming task, and advances in LLM capabilities have made using LLMs in annotation attractive (Wang et al., 2021). Complex, theory-driven text analysis is increasingly being mediated by LLMs (De Paoli, 2023) or LLM-powered tools (Lam et al., 2024).

Given all this progress, LLMs have created opportunities to create annotation pipelines that appear to work off the shelf without fine-tuning, making automated annotation accessible to practitioners with less technical skill. LLMs' reported performance in annotating socially complex topics (Gilardi et al., 2023), sometimes with greater skill than humans (He et al., 2024), potentially opens LLM-based annotation to an even wider range of fields and practices compared to past years. This makes understanding the many ways humans may interact with LLM annotations more important.

With the relative ease of creating LLM annotations for a variety of tasks, there is a temptation to just put a "human in the loop" to check annotations and ensure the model's outputs are "reasonable and reliable" (Wang et al., 2025) in order to approve LLM annotations of a social concept. But given that we know humans are subject to anchoring bias—the bias towards the first option we are presented (Tversky and Kahneman, 1974)—humans may review and confirm LLM annotations that are plausible, but nonetheless significantly change 1) the annotation evaluation process and 2) the out-

come the annotations get used for (such as the decision boundary for classification judgments, or the distribution of annotations used in a text analysis), downstream.

In this work, we ask several questions. First, when provided with (different forms of) LLM assistance, do crowdworker annotators "produce more" by going faster in a complex, subjective annotation task, and does this result in them "understanding less?" Do they find LLM suggestions accurate and helpful, and how often do annotators take these suggestions? If annotations influenced by LLM suggestions are used to construct ground truth on annotation tasks involving complex social concepts, what effect does that have on evaluated performance of these LLMs on those annotation tasks?

We use two community conversation datasets to address these questions, recruiting crowdworkers to annotate the data according to a list of identified themes. These workers are presented with LLM-suggested annotations in a variety of formats. We then study how the crowdworkers use these LLM suggestions in a complex annotation process in service of answering these research questions.

Our findings open up questions regarding the use of AI assistance in qualitative research where annotators act as independent reviewers of AI suggestions and can supposedly still retain full control of the analysis. We believe our work underlines the importance of understanding the impact of LLM-assisted annotation on subjective, qualitative tasks, on the creation of gold data for training and testing, and on the evaluation of NLP systems on subjective tasks. In addition to the findings that answer the aforementioned questions, we release a dataset of human and LLM-assisted annotations on two complex qualitative codebooks across a variety of conditions.

2 Related Work

LLMs have been increasingly employed in various "human in the loop" AI assistance setups, e.g., in education (Jiang et al., 2024), and coding (Mozannar et al., 2024). LLMs have also been used for annotation tasks, for reasons like decreasing labeling cost (Wang et al., 2021). Ziems et al. (2023) discussed how LLMs are being widely used in computational social science tasks, including subjective tasks. Li et al. (2023) found that the performance of LLMs trained on synthetically generated ground truth data is negatively associated with the subjectivity of the task. More work has shown the challenges of LLM annotation: LLM annotation performance can be highly variable to prompts (Atreja et al., 2024) and can depend on the ordering of choices presented in a prompt. (Wang et al., 2023; Liu et al., 2023).

While using LLMs to create annotations may have "good enough" performance and likely does decrease cost compared to hiring human crowd workers, many tasks still require humans to still be in the loop, especially for subjective annotation and analysis tasks; some methods suggest ways of using humans in the loop to optimize prompts for LLM annotation (Pangakis and Wolken, 2024). Many AI-assisted text annotation platforms have also been developed and published within the HCI space (Overney et al., 2024; Gao et al., 2024, 2023a, 2025). Research shows AI-suggested labeling platforms increase agreement and convergence on qualitative codes, or text labels (Gao et al., 2023b).

There is increasing evidence that humans tend to anchor on the suggestions that AI systems give, which can result in changes to communication and even user opinions (Jakesch et al., 2019). Some work observed how humans anchor on LLM outputs in text analysis tasks, including topic induction. For instance, Choi et al. (2024) show that in a topic generation task, analysts anchor on LLM outputs, resulting in different topic lists depending on whether or not they saw the LLM versions. This illustrates the potential risk of homogenization of insight as a result of AI influence on text analysis. This concern is raised by Messeri and Crockett (2024) regarding AI's influence on science more generally, and the authors discuss LLMs' potential to reduce diversity in human judgment, creating an environment in science where we "produce more but understand less."

Many cite time savings as their motivation for using LLMs as annotators, however, findings have so far been mixed regarding productivity. For example, Bughin shows that while AI can boost coding productivity, there exists a tradeoff between productivity and coding quality, and Overney et al. observed that users with AI support in the SenseMate platform spent more time on qualitatively coding data.

Here, we examine how presenting LLM-generated suggestions to annotators in a complex subjective annotation task affects their understanding of the task as well as their suggestion uptake, with implications for the evaluation of LLM performance on these tasks, even when humans are put

"in the loop" to review and confirm annotations.

3 Data and Codebook

We source two conversation collections from the Fora corpus (Schroeder et al., 2024). In 2022, the NYC Department of Health & Mental Hygiene, the NYC Public Health Corps (PHC), and the national non-profit Cortico recruited over 100 communities to a series of 28 small group dialogues hosted in New York City to understand community resourcing and vaccine decisions during COVID-19. Following the conversations, community workers created a codebook of themes of interest to the "NYC" corpus (as we will call it), then labeled quotes from the conversations with the themes denoted by the codebook. Similarly, in 2021, a conversation series in Boston called "Real Talk for Change" was hosted to understand issues in marginalized communities leading up to the 2021 Boston Mayoral election. We use the conversation data and codebook created for this "RTFC" corpus as well.

The NYC codebook developed by community partners had seven overarching themes related to health and vaccine decisions, including *External Motivations: Friends & Family*, *Intrinsic Motivations: Not wanting to get the virus*, and *Role of Community Health Organizations: Health Education & Support*, and *Vaccine Hesitancy*. Each top-level label had sublabels, for a total of 27 total labels related to the NYC corpus. Similarly, the RTFC corpus has 9 overarching top-level labels, and 41 sublabels relevant to the corpus, such as *Safety: Street violence* and *Housing: Housing affordability*. The full codebook for each corpus is available in the appendix. We sampled 200 quotes from the NYC corpus as the main data set for this study, and 200 quotes from the Real Talk for Change corpus as a replication data set. Excerpts had an average length of 592 characters.

4 Methods

The experiment compares the annotation of 200 quotes by 5 annotators each according to the codebook for both NYCDOMH and RTFC. First, we create a crowdworker "baseline" for the annotation task without LLM assistance for both corpora. Following typical practices, we construct a ground truth set of labels using a 3/5 majority vote for each label. We then test how this crowd baseline contrasts to annotations provided through three distinct ways of presenting LLM-suggested labels for annotators to review. As such, the four experimental conditions testing how *interface* mediated LLM-assisted annotation suggestions were:

- **Condition 1: Baseline.** Annotators were not shown any LLM-generated suggestions in the annotation task.
- **Condition 2: Text-based suggestions.** Annotators were presented with the annotation interface, which presented the text to be annotated at the top of the screen. The text "Suggested tags:" was appended after the quote, followed by a list of LLM-generated labels, generated either by GPT-4 or LLaMA, according to the corpus' codebook of labels.
- **Condition 3: Text-based suggestions, with AI disclosure** Same as Condition 2, except immediately following the quote, the text "Suggested tags from AI:" was appended, followed by the list of LLM-generated labels, pictured in pictured in Figure 8.
- **Condition 4: Pre-highlighted labels in interface** LLM-generated label suggestions were pre-highlighted on each question in the interface, as pictured in Figure 9.

These conditions provide a sliding scale of assistance to an annotator. The no-assistance baseline in Condition 1 provide the basis for crowd truth labels. Text-based suggestions provide some assistance, but still require the annotators to read the information then integrate the suggestions themselves into decisions for each annotation question. Condition 3 was the same as Condition 2 with the exception of including a disclosure that the suggestions were from "AI." We included this condition to test whether annotators would change their perception of or behavior towards suggestions if they knew the origin of them— either in their perceived quality or in their rate of uptake. Finally, Condition 4 provided annotators with the strongest suggestion, drawing the annotator's attention directly to a colored highlight of the suggested label. These conditions were all shown to annotators through a deployment of the open source annotation interface, Potato (Pei et al., 2023). Screenshots and interface examples are in the appendix.

We ran these conditions on the NYC data with GPT-generated labels, and we replicated label suggestions created by LLaMA (Touvron et al., 2023),

an open-source model. Second, we also create a no-assistance baseline for the RTFC data, and replicated the experiment on label suggestions created by GPT-4 to test generalizability to a different codebook and dataset.

We generated label suggestions by prompting one of two LLMs. For our main experiment, we used OpenAI's API to prompt GPT-4 (OpenAI et al., 2024), model version `gpt-4-1106-preview`, zero shot, and for our replication study, we used LLaMA `llama3-8b` (Touvron et al., 2023), accessed through the service LlamaAPI. We used the same prompt style and instructions to prompt both GPT-4 and LLaMA, which were prompted once per quotation to produce a list of labels for each of the 200 quotations from the NYC and RTFC corpora. The prompt details for each task are available in the appendix.

4.1 Survey experiment

In order to test annotation performance under a variety of conditions, we hired crowdworkers to complete our annotation study. We recruited qualified annotators from Prolific, and additional details about recruitment are available in the appendix.

Once annotators accepted the task and had instructions, each annotator was given 20 unique annotations, with 2 randomly assigned "understanding" check questions mixed in. 200 quotes were thus annotated by 5 unique annotators in each of the four experimental conditions. Each annotator participated in just one experimental condition. Each annotator was recommended to spend 20-30 minutes on the annotation task, and spent an average of 35 minutes on the task.

Prior to doing the task, we conducted an exercise to measure inter-annotator agreement among Prolific workers in our worker pool for this task. In order to do so, we presented 15 unique annotators with 19 unique quotes from the NYC corpus, and 20 unique annotators with 20 quotes from the RTFC corpus. We then measured inter-rater reliability on the codes for each corpus using the traditional measure of Krippendorff's alpha (α) across annotators, which yielded low to medium levels of agreement across annotators overall, depending on the label. Overall low to medium agreement in this context is unsurprising for both the NYC and RTFC codebooks, given the subjective, complex nature of each task. In order test basic understanding of the task, we ranked quote and label pairs by level of agreement in the IRR task. We selected these extremely high-agreement quote and label pairs as a pool of minimum-threshold understanding questions for annotator, which we used as proxies for basic understanding of the task. The 4 selected test questions in the NYC corpus had 13 or 14 of 15 annotators in agreement with the label, and 15-18 annotators in agreement in the RTFC corpus. We included two randomly selected understanding test questions from the relevant corpus in the question bank for each annotator, which were presented in a random order within the task, and called "understanding" questions for the rest of this study.

Within the presented task, each annotator would see a quotation from the corpus on the screen. Annotators were prompted to select any labels that applied to the quote, or select none if none applied. For the NYC corpus, there were 7 annotation questions for each quotation, one corresponding to each top-level label. In the RTFC corpus, there were 9 annotation questions for each quotation, corresponding to each top-level label.

In the conditions where LLM-generated suggestions were presented to the annotator, we also included an additional question associated with each quotation, asking annotators if suggestions were "overall," "somewhat," or "not helpful/accurate."

Following all presented quotes, we presented annotators with a post survey in order to understand their perception of the task. Before answering these self-report questions, we told them "Your answer to this question will not reflect on your performance, so please answer honestly." Annotators were given the opportunity to answer the following, rating each on a 1-5 scale, with 5 being the highest:

- How well do you feel you understood this labeling task?
- Overall, how confident do you feel in your answers on this task?
- After doing this task, how well do you understand the concerns and priorities of this community?
- After doing this task, how well could you explain this community's concerns and needs?

We finished the post-survey with some demographic questions to better understand the annotator pool after their answers had already been given, including asking annotators for their race, gender, political orientation.

5 Results

We compare outcomes on these annotation tasks across 4 conditions, including 3 assistance condi-

Dataset	Model	Suggestion type	Avrg. minutes
NYC	None	None (Baseline)	25.5
	GPT	Text-based	28.4
		Text-based, AI origin disclosed	30.8
		Pre-filled	30.1
	LLaMA	Text-based	32
RTFC	None	None (Baseline)	34
	GPT	Text-based	35.4

Table 1: Time spent on 20 annotations across conditions.

tions, 2 corpora (NYC and RTFC), and 2 models that provided suggestions (GPT-4 and LLaMA).

5.1 LLM assistance did not decrease annotation time

Contrary to our pre-registered hypothesis, we found annotators in the LLM assistance conditions did not go faster than annotators in the baseline condition. To calculate time spent on the task, we subset to annotators who completed all 20 annotations, and removed test questions and post-survey questions. This gave us time spent on 20 substantive annotations in the task. In two of the LLM assistance conditions for the NYC data, there was a statistically significant increase of 5 minutes spent on the annotation task compared to baseline.

In the assistance conditions, we included an additional short question for each annotation asking annotators to rate suggestion quality. Small time increases in the assistance conditions may be attributable to this additional question we asked. Figure 2 in the appendix shows time variation. This replicates findings in Overney et al., which found that when qualitative coders had access to AI-generated suggestions for qualitative codes, they actually spent longer on the annotation task than in the baseline condition.

5.2 Assistance improves self-reported understanding of task and content

Despite no increase in time-based productivity outcomes, annotators' self-reported experience of the task improved in many of the assistance conditions. Annotators self-reported higher levels of task understanding, task confidence, community understanding, and ability to explain community needs over the baseline no-assistance condition, and many had statistically significantly higher levels ($p < .01$) over the baseline condition according to a two-tailed t-test, with medium positive effect sizes calculated using Cohen's D.[1] Improvements over no-assistance baselines were strongest for annotators' self-reported "understanding of the community" and "ability to explain the community's needs," and these are the two outcome measures with strong replication on the RTFC corpus as well.

Because this is a subjective task, self-reports of understanding could theoretically increase with LLM assistance while some measure of "true" understanding on the task could decrease. We found that pass rates on the "understanding" checks we included in the task did not statistically significantly change (either increase or decrease) in the LLM assistance conditions, providing at least basic assurance that providing assistance did not immediately elicit overreliance on the assistancen to the point the basic task was not understood.

5.3 Annotators overwhelmingly like and take the suggestions

We converted annotator ratings of suggestion helpfulness and accuracy into numeric values as follows: "Overall helpful/accurate" to a 2, "Somewhat helpful/accurate" to a 1, and "Not helpful/accurate" to a 0. Across conditions, LLM suggestions were rated as between somewhat and very helpful (mean: 1.49, details in appendix). We did not find statistically significant differences in ratings of helpfulness between GPT-4 and Llama, or in the way suggestions were presented (Condition 2: text-based, Condition 3: text-based + AI disclosed, and Condition: pre-filled). Helpfulness of label suggestions was also rated similarly in the NYC and RTFC annotation tasks, suggesting no one model worked better than the other, and the assistance was helpful in two different labeling contexts.

Reflecting this perceived helpfulness and accuracy, we observed strong LLM suggestion uptake across annotators. To observe suggestion uptake rates at the individual level and in contrast to a crowd baseline, we obtained the set intersection of labels applied by the LLM to a particular quote and the set of labels applied by a crowd decision of human annotators to that same quote. Crowd decisions for labels were made by checking if, for each labels, the labels was assigned to the quote by at least 3 (of the 5) annotators, giving a final list of labels for the quote on which at least 3 annotators agreed to its applicability. We repeated this process at a crowd decision threshold of 4 annotators, as well as full consensus of all 5 annotators.

For each crowd decision threshold, we divided the size of the set intersection of labels with LLM-suggested labels by the total number of labels applied by the LLM. This gave a percentage of an-

[1] Details available in the appendix.

notator label overlap with the LLM suggestions at three crowd decision thresholds. Treating crowd decisions on the unassisted baseline condition for the NYC corpus as ground truth, just 40% of labels given by a crowd decision of 3 annotators overlapped with the GPT-4 suggestions. This further dropped sharply to 24% when the crowd threshold is raised to 4 annotators, and to just 8% when raised to full consensus of 5 annotators.

Figure 1 shows that in all LLM assistance conditions, run for Conditions 2, 3, and 4 with GPT-4 labels on NYC data, the overlap between the crowd ground truth created with LLM assistance and the LLM label set increased dramatically. We display this in terms of different crowd decision thresholds. At a crowd decision threshold of 3/5, crowd labels the average rate of overlap between crowd labels and suggested labels was 81-89% depending on the presentation of suggestions, 54-67% at a crowd decision threshold of 4, and between 24-40% for full crowd consensus of 5. In other words, overlap with LLM suggestions increased 40% at the typical decision threshold of 3 when human annotators were given these suggestions to review, a statistically significant increase according to a two-tailed t test at $p = .05$. Text-based Llama suggestions resulted in similar results for the NYC corpus, as did GPT-4 suggestions on the RTFC corpus. Details on these findings are in the appendix.

We also observed consensus agreement of all 5 annotators was significantly more likely in Condition 4, where suggestions were presented most strongly by appearing pre-filled in the interface. We observed that full consensus, or full agreement by all 5 annotators, increase from just 8% in the no assistance baseline to 43% in the pre-highlighted label condition. Using a two-tailed t-test, we find this is a statistically significant increase a $p = .001$, including Bonferroni correction for multiple comparisons.

5.4 Using human-reviewed, LLM-assisted labels as ground truth significantly inflates reported model performance

Using LLMs to annotate or augment annotations that can be used to train models or evaluate model performance is tempting, given the challenge of scaling annotation, particularly for subjective tasks that may be challenging for crowd workers. How much does model performance appear to improve on these subjective tasks when we use LLM-assisted annotations reviewed by humans as ground truth?

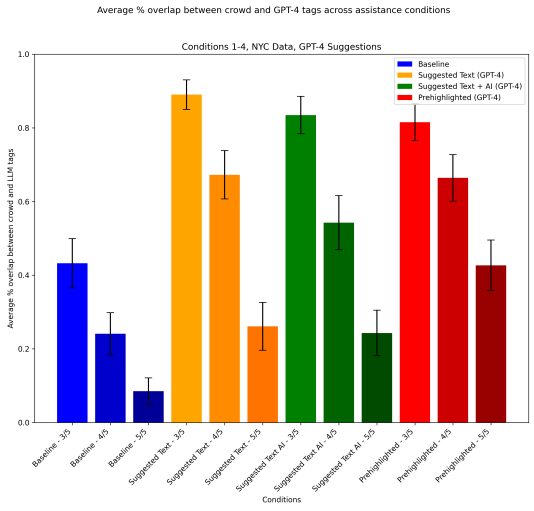

Figure 1: Percent overlap of annotator labels with LLM-suggested labels by condition and crowd decision threshold

To examine this, we first created baseline ground truth labels for the 27 NYC labels, by aggregating the 5 annotations made by each annotator into a 3/5 majority vote to assign each label. For each label, we calculate an F1 score of "model performance" using the human crowd labels as ground truth, and compare to either the GPT labels or Llama labels for the entire set of 200 NYC quotations, calculating an F1 score of model performance. Using baseline human ground truth shows overall low performance on these labeling tasks, with similar performance for both GPT-4 and Llama: the average weighted F1 score of GPT-4 performance across all labels is .44 ($\sigma = .17$) when using the human crowd labels as ground truth, and .42 ($\sigma = .17$) for Llama when using the human crowd labels as ground truth. Interestingly, when GPT-4 labels for the NYC corpus are used as ground truth labels and compared to Llama labels, the average F1 score is significantly higher at .62 ($\sigma = .10$) compared to performance when using a human baseline. The individual breakdown of label-level performance is available in Table 2, and breakdowns of GPT-4 versus Llama are available in the appendix in Table 5.

We next aggregated labels from annotators reviewing text-based suggestions from GPT-4 ("GPT-assisted") or Llama ("Llama-assisted"). We used a 3/5 majority to approve each label, constructing a new ground truth condition for annotations made with assistance. When using the GPT-assisted ground truth, the average weighted F1 score of

GPT-4 performance across all labels increased to .75 ($\sigma = .14$), for an average increase in F1 score of +.31. When using crowd-aggregated "Llama-assisted" labels as ground truth, the average weighted F1 score of Llama performance across all labels increased to .72 ($\sigma = .16$), for a similar average increase in F1 score of +30. Performance on some labels increased by substantially more than that average, including "Role of community organizations: Trust, Rapport, & Relationships," which increased from .20 to .75 when GPT-4's labeling performance was evaluated on GPT-assisted ground truth labels.

6 Discussion

While mainstream perceptions suggest LLMs can help speed up annotation, we find that if humans review individual LLM-generated suggestions, annotation time does not decrease. From our own measures, we find annotators who were given assistance self-reported improved task understanding, and baseline task understanding, as measured through test questions, remained constant across conditions. Follow-up work could examine if seeing AI suggestions sometimes increased task time because there was more information to process, and if suggestions may teach new annotators to do a complex task, increasing their confidence when assistance is given. Future work can also examine whether annotators under a different compensation incentive structure approve LLM suggestions more quickly than these workers did.

Annotation is usually the first step in creating ground truth data for evaluating a model's performance on an NLP task. Complex, subjective tasks are common in the subfield of NLP for computational social science and cultural analytics. Using LLMs to annotate data used for training and evaluation of a task is attractive due to time and cost efficiency compared to hiring humans, who may noisily interpret a subjective task like this one. However, our findings provide a cautionary note: humans often take LLM suggestions they are given, even when a human individually reviews each label that contributes to the ground truth. As such, using LLM annotations, or LLM-assisted labels like those described here inflates measures of LLM performance on these subjective annotation tasks.

In taking LLM suggestions, annotators homogenize "ground truth" on these tasks towards LLM baselines. In NLP for CSS tasks and in qualitative coding, using labels to measure prevalence of a concept in text is common, so LLM suggestions can change these measurements. For example, imagine using these annotions to analyze cited reasons for vaccine hesitancy given by participants in the NYC conversations. We could view the list of most commonly co-occurring labels with *Did not vaccinate*. In the human baseline, *External motivations: Family & Friends* was the second most common co-occurring label, whereas in the LLM baseline, it was the sixth, occurring 25% less often than in the human baseline. In the GPT-assisted annotation condition, *External motivations: Family & Friends* also drops to the sixth most commonly co-occurring label, mirroring the LLM's label distribution rather than the original human baseline. Analysts using LLM-assisted annotations could thus come to a different conclusion about the relative importance of *Family & Friends* in motivating vaccine hesitancy compared to the human-only baseline.

Homogenization towards an LLM baseline may not be an inherent problem, but the low performance we observe from both GPT-4 and Llama when contrasted with a human baseline suggests that LLMs use a different background concept (Jacobs and Wallach, 2021) for annotating some labels than human crowdworkers do. For example, given a starting F1 score of just .2 comparing LLM annotations to the human crowd baseline, GPT-4 must operationalize the identification *Health Education and Support* differently than crowdworkers did. When LLM annotations are used to identify this construct, annotations are thus measuring something different than the humans crowd baseline does, and the background concept of *Health Education and Support* being annotated becomes *more* like the LLM's conception of *Health Education and Support* when annotators have its assistance.

LLM assistance also inherently increases measures of interrater reliability when the same LLM assistance is given across annotators. IRR measures are used as a positive signal of reliability when humans annotate social science concepts (McDonald et al., 2019). However, for increased IRR across annotators when using LLM assistance to be a positive outcome of LLM assistance on annotation, researchers would need to be confident that the LLM baseline— and the way it operationalizes each background concept being identified— is *more correct* than human judgments. In subjective tasks, this can be hard to verify and prove, but error

Top-level label	Sublabel	Frequency	Ground truth v. LLM, weighted F1 score			
			Human crowd v. GPT labels	Human crowd v. Llama labels	GPT-assisted human labels vs GPT labels	Llama-assisted human labels vs Llama labels
External motivations	Civic Organizations	32	0.60	0.49	0.87 +.27	0.79 +.30
	Employers	8	0.50	0.50	0.84 +.34	0.79 +.29
	Family & Friends	36	0.52	0.53	0.76 +.24	0.82 +.29
	Health Care Providers	20	0.53	0.49	0.89 +.36	0.75 +.26
	Social & News Media	8	0.32	0.46	0.73 +.41	0.87 +.41
Future visions & Takeaways	Discussion of post-pandemic future	16	0.73	0.59	0.79 +.06	0.84 +.25
	Reflections on the conversation	19	0.15	0.00	0.36 +.21	0.24 +.21
Intrinsic motivations	Basing decisions on data	6	0.42	0.33	0.81 +.39	0.87 +.47
	Getting back to normal	28	0.38	0.44	0.76 +.38	0.65 +.21
	Not wanting to get the virus	28	0.48	0.49	0.92 +.44	0.90 +.41
Personal COVID experience	Resilience, Connection, & Hope	35	0.32	0.26	0.60 +.28	0.66 +.40
	Stress, Fear, & Uncertainty	56	0.66	0.61	0.86 +.20	0.84 +.23
Resources that helped	Significant Impact Resources that helped	34	0.64	0.63	0.84 +.20	0.71+.08
	Unmet community needs	24	0.42	0.46	0.50 +.08	0.67 +.21
Role of community organizations	Health Education & Support	23	0.20	0.26	0.68 +.48	0.56 +.30
	Incentives	6	0.28	0.29	0.67 +.39	0.64 +.35
	Reducing barriers	8	0.35	0.33	0.78 +.43	0.81 +.48
	Trust, Rapport, & Relationships	22	0.20	0.20	0.75 +.55	0.62 +.42
Vaccine hesitancy	Did not vaccinate	3	0.60	0.40	0.77 +.17	0.57 +.17
	Mistrust or Skepticism	23	0.57	0.71	0.93 +.36	0.88 +.17

Table 2: Performance evaluation of human crowd labels against GPT labels and Llama labels, then GPT-assisted human labels against GPT labels and Llama-assisted human labels against Llama labels. **Frequency** refers to n observations found across crowd-aggregated annotations on the 200 quotations from the NYC corpus. Performance increases an average of +30% when using LLM-assisted crowd labels compared to an unassisted crowd baseline.

analysis of specific ambiguous labels may help.

Second, there are many tasks in NLP where varied annotator perspective can be valuable (Cabitza et al., 2023; Plank, 2022), both for the reason of constructing a robust ground truth (Aroyo, 2013; Yan et al., 2014), or for representing diverse human perspectives on a complex social construct like hate speech (Sap et al., 2022). In qualitative research, some traditions embrace divergent annotator perspective as well in order to widen insight in qualitative annotation (McDonald et al., 2019). In both the cases of creating ground truth for NLP tasks and qualitative annotation, practitioners should know that using or providing LLM assistance to annotators will likely result in lessened variation.

Given potential consequences for representation and construct validity that vary by task, researchers should only proceed with LLM-assisted annotation with a level of caution appropriate to their task and goal. They should recognize that using LLM assistance to construct ground truth labels inflates perceptions of model performance on that task, even when humans review them and individual judgments are aggregated into a crowd ground truth. Follow-up work can investigate if these findings hold for a similarly complex annotation task, a less complex annotation task, and when employing expert annotators rather than inexperienced crowd workers. Homogenization effects may be lessened by presenting information about model confidence, or alternative ideas, and not just a single set of suggestions.

7 Conclusion

In a pre-registered experiment with 350 unique annotators and 7,000 annotations across 4 conditions, 2 models, and 2 datasets, we find that presenting crowdworkers with LLM-generated annotation suggestions did not make them faster, but did improve their self-reported confidence in the task. Annotators strongly uptook suggestions, changing the label distribution to more closely resemble the LLM's proposed distribution.

Strikingly, we found that using LLM-assisted labels to evaluate model performance resulted in much higher reported F1 scores than when using a human crowd baseline, with increases in F1 scores for model performance on some labels by as much as +x.56. Obviously, using labels influenced by the model to evaluate the model is not standard or advisable in classic evaluation paradigms. However, in the many systems being created that "just put a human in the loop" to review LLM annotation outputs, this paradigm of reviewing LLM outputs to "approve" them is increasingly likely to occur. Practitioners should know that, especially in subjective tasks, simply reviewing LLM suggestions will nudge the distribution of label outputs towards an LLM baseline, even if humans are given a change to review the outputs.

8 Limitations

Crowdworkers may be particularly susceptible to this kind of influence from LLM suggestions, however, their continued employment as a standard for annotation in the field justifies their employment in the task here on a deliberately ambiguous task. Furthermore, different results may be reached with specialized annotators with particular domain knowledge. Annotators with a relationship to the data, including a relationship to the community of interest, may also shape how they align with or reject AI interpretations of the data. Follow-up work can investigate whether domain experts have less anchoring bias than we observed here, and whether they confidently defect from LLM suggestions when needed.

References

Lora Aroyo. 2013. Crowd Truth: Harnessing disagreement in crowdsourcing a relation extraction gold standard. page 0 Bytes. figshare. Artwork Size: 0 Bytes.

Shubham Atreja, Joshua Ashkinaze, Lingyao Li, Julia Mendelsohn, and Libby Hemphill. 2024. Prompt Design Matters for Computational Social Science Tasks but in Unpredictable Ways. *arXiv preprint*. ArXiv:2406.11980 [cs].

Jacques Bughin. 2024. The role of firm ai capabilities in generative ai-pair coding. *Journal of Decision Systems*, 0(0):1–22.

Federico Cabitza, Andrea Campagner, and Valerio Basile. 2023. Toward a Perspectivist Turn in Ground Truthing for Predictive Computing. *Proceedings of the AAAI Conference on Artificial Intelligence*, 37(6):6860–6868. Number: 6.

Alexander S. Choi, Syeda Sabrina Akter, JP Singh, and Antonios Anastasopoulos. 2024. The llm effect: Are humans truly using llms, or are they being influenced by them instead? *Preprint*, arXiv:2410.04699.

Stefano De Paoli. 2023. Can Large Language Models emulate an inductive Thematic Analysis of semi-structured interviews? An exploration and provocation on the limits of the approach and the model. *arXiv preprint*. ArXiv:2305.13014 [cs].

Jessica L. Feuston and Jed R. Brubaker. 2021. Putting Tools in Their Place: The Role of Time and Perspective in Human-AI Collaboration for Qualitative Analysis. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2):1–25.

Jie Gao, Kenny Tsu Wei Choo, Junming Cao, Roy Ka-Wei Lee, and Simon Perrault. 2023a. CoAIcoder: Examining the Effectiveness of AI-assisted Human-to-Human Collaboration in Qualitative Analysis. *ACM Transactions on Computer-Human Interaction*, 31(1):6:1–6:38.

Jie Gao, Kenny Tsu Wei Choo, Junming Cao, Roy Ka-Wei Lee, and Simon Perrault. 2023b. Coaicoder: Examining the effectiveness of ai-assisted human-to-human collaboration in qualitative analysis. *ACM Trans. Comput.-Hum. Interact.*, 31(1).

Jie Gao, Yuchen Guo, Gionnieve Lim, Tianqin Zhang, Zheng Zhang, Toby Jia-Jun Li, and Simon Tangi Perrault. 2024. CollabCoder: A Lower-barrier, Rigorous Workflow for Inductive Collaborative Qualitative Analysis with Large Language Models. *arXiv preprint*. ArXiv:2304.07366 [cs].

Jie Gao, Zhiyao Shu, and Shun Yi Yeo. 2025. Using Large Language Model to Support Flexible and Structural Inductive Qualitative Analysis. *arXiv preprint*. ArXiv:2501.00775 [cs].

Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. 2023. ChatGPT outperforms crowd workers for text-annotation tasks. *Proceedings of the National Academy of Sciences*, 120(30):e2305016120. Publisher: Proceedings of the National Academy of Sciences.

Zeyu He, Chieh-Yang Huang, Chien-Kuang Cornelia Ding, Shaurya Rohatgi, and Ting-Hao Kenneth Huang. 2024. If in a Crowdsourced Data Annotation Pipeline, a GPT-4. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, pages 1–25, New York, NY, USA. Association for Computing Machinery.

Abigail Z. Jacobs and Hanna Wallach. 2021. Measurement and Fairness. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '21, pages 375–385, New York, NY, USA. Association for Computing Machinery.

Maurice Jakesch, Megan French, Xiao Ma, Jeffrey T. Hancock, and Mor Naaman. 2019. Ai-mediated communication: How the perception that profile text was written by ai affects trustworthiness. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, page 1–13, New York, NY, USA. Association for Computing Machinery.

Hang Jiang, Xiajie Zhang, Robert Mahari, Daniel Kessler, Eric Ma, Tal August, Irene Li, Alex Pentland, Yoon Kim, Deb Roy, and Jad Kabbara. 2024. Leveraging large language models for learning complex legal concepts through storytelling. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7194–7219, Bangkok, Thailand. Association for Computational Linguistics.

Jialun Aaron Jiang, Kandrea Wade, Casey Fiesler, and Jed R. Brubaker. 2021. Supporting Serendipity: Opportunities and Challenges for Human-AI Collaboration in Qualitative Analysis. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1):1–23. ArXiv:2102.03702 [cs].

Michelle S. Lam, Janice Teoh, James A. Landay, Jeffrey Heer, and Michael S. Bernstein. 2024. Concept Induction: Analyzing Unstructured Text with High-Level Concepts Using LLooM. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pages 1–28, Honolulu HI USA. ACM.

Zhuoyan Li, Hangxiao Zhu, Zhuoran Lu, and Ming Yin. 2023. Synthetic Data Generation with Large Language Models for Text Classification: Potential and Limitations. *arXiv preprint*. ArXiv:2310.07849 [cs].

Nelson F. Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. 2023. Lost in the middle: How language models use long contexts. *Preprint*, arXiv:2307.03172.

Nora McDonald, Sarita Schoenebeck, and Andrea Forte. 2019. Reliability and Inter-rater Reliability in Qualitative Research: Norms and Guidelines for CSCW and HCI Practice. *Proc. ACM Hum.-Comput. Interact.*, 3(CSCW):72:1–72:23.

Lisa Messeri and M. J. Crockett. 2024. Artificial intelligence and illusions of understanding in scientific research. *Nature*, 627(8002):49–58. Publisher: Nature Publishing Group.

Hussein Mozannar, Gagan Bansal, Adam Fourney, and Eric Horvitz. 2024. When to show a suggestion? integrating human feedback in ai-assisted programming. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 10137–10144.

OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, C. J. Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. GPT-4 Technical Report. *arXiv preprint*. ArXiv:2303.08774 [cs].

Cassandra Overney, Belén Saldías, Dimitra Dimitrakopoulou, and Deb Roy. 2024. SenseMate: An Accessible and Beginner-Friendly Human-AI Platform for Qualitative Data Analysis. In *Proceedings of the 29th International Conference on Intelligent*

User Interfaces, pages 922–939, Greenville SC USA. ACM.

Nicholas Pangakis and Samuel Wolken. 2024. Keeping Humans in the Loop: Human-Centered Automated Annotation with Generative AI. Publisher: arXiv Version Number: 2.

Jiaxin Pei, Aparna Ananthasubramaniam, Xingyao Wang, Naitian Zhou, Jackson Sargent, Apostolos Dedeloudis, and David Jurgens. 2023. POTATO: The Portable Text Annotation Tool. *arXiv preprint*. ArXiv:2212.08620 [cs].

Barbara Plank. 2022. The "Problem" of Human Label Variation: On Ground Truth in Data, Modeling and Evaluation. *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 10671–10682. Conference Name: Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing Place: Abu Dhabi, United Arab Emirates Publisher: Association for Computational Linguistics.

Maarten Sap, Swabha Swayamdipta, Laura Vianna, Xuhui Zhou, Yejin Choi, and Noah A. Smith. 2022. Annotators with Attitudes: How Annotator Beliefs And Identities Bias Toxic Language Detection. *arXiv preprint*. ArXiv:2111.07997 [cs].

Hope Schroeder, Deb Roy, and Jad Kabbara. 2024. Fora: A corpus and framework for the study of facilitated dialogue. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13985–14001, Bangkok, Thailand. Association for Computational Linguistics.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. LLaMA: Open and Efficient Foundation Language Models. *arXiv preprint*. ArXiv:2302.13971 [cs].

Amos Tversky and Daniel Kahneman. 1974. Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131.

Jenny S. Wang, Samar Haider, Amir Tohidi, Anushkaa Gupta, Yuxuan Zhang, Chris Callison-Burch, David Rothschild, and Duncan J. Watts. 2025. Media Bias Detector: Designing and Implementing a Tool for Real-Time Selection and Framing Bias Analysis in News Coverage. ArXiv:2502.06009 [cs].

Shuohang Wang, Yang Liu, Yichong Xu, Chenguang Zhu, and Michael Zeng. 2021. Want To Reduce Labeling Cost? GPT-3 Can Help. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 4195–4205, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Yiwei Wang, Yujun Cai, Muhao Chen, Yuxuan Liang, and Bryan Hooi. 2023. Primacy Effect of ChatGPT. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 108–115, Singapore. Association for Computational Linguistics.

Yan Yan, Rómer Rosales, Glenn Fung, Ramanathan Subramanian, and Jennifer Dy. 2014. Learning from multiple annotators with varying expertise. *Machine Learning*, 95(3):291–327.

Caleb Ziems, William Held, Omar Shaikh, Jiaao Chen, Zhehao Zhang, and Diyi Yang. 2023. Can Large Language Models Transform Computational Social Science? *arXiv preprint*. ArXiv:2305.03514 [cs].

A Corpus details

Corpora were selected based on the availability of both public conversation data within Fora (Schroeder et al., 2024), and the existence of a human-created codebook for annotation which was shared with us by our collaborating organizational partner. The Fora corpus is lightly anonymized, with speaker names removed. For the NYC and RTFC sample of 200 quotations, we manually reviewed and removed any personally identifiable information before using it in a prompt to either model, and before showing it to annotators. Participants in the NYC and RTFC conversation collections were aware their voices would be collected and used to inform the public about issues in their community, as well as potentially used in research. Both the NYC and RTFC conversations contain a mix of standard American English and African American English, as well as Spanish, though less often. We eliminated any participant comments in Spanish prior to sampling 200 comments for this study, given that performance on this tasks could not be compared across languages, and the codebook was developed in English. Given the unreliability of African American English dialect detectors as of the time of this submission, particularly on transcribed speech, we are not able to estimate prevalence of African American English or other dialects that may be in this corpus. Demographic information of speakers was not collected in the NYC or RTFC conversation corpora, but more details on the corpora are available in the Fora corpus.

B Additional results

In addition to Table1, we provide a visualization of time taken on Conditions 1-4 on the NYC corpus with LLM suggestions from GPT-4 in Table3.

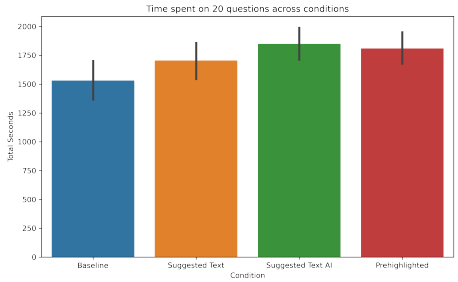

Figure 2: Time (number of seconds) spent by annotators on the task, for Conditions 1-4 on NYC data.

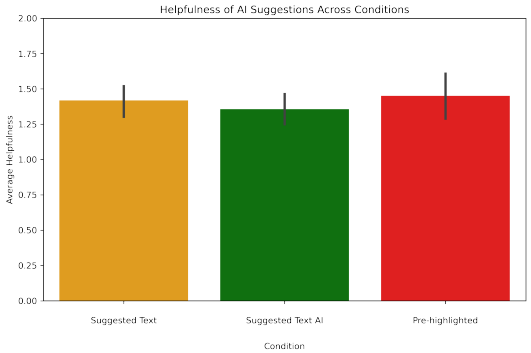

Figure 3: Annotator perception of suggestion helpfulness by condition

As shown in Figure3, annotators perceived GPT-4 suggestions in Conditions 2, 3, and 4 on the NYC corpus to be between somewhat and very helpful.

Corpus	Assistance type	Assistance Model	Average Helpfulness	Std
NYC	Text-based	GPT-4	1.42	.42
NYC	Text-based	Llama	1.3	.38
NYC	Text-based, AI disclosed	GPT-4	1.36	.42
NYC	Pre-filled	GPT-4	1.45	.62
RTFC	Text-based	GPT-4	1.49	.37

Table 3: Helpfulness of suggestions across conditions

Text-based suggestions from GPT-4 were rated as similarly helpful on RTFC data.

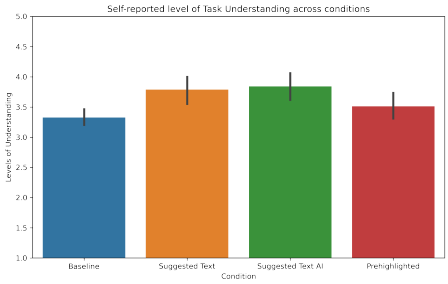

Figure 4: Self-reported task understanding by condition

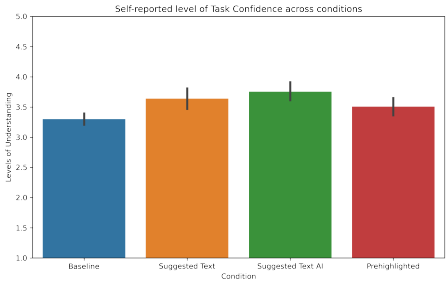

Figure 5: Self-reported task confidence by condition. Conditions 1-4 on NYC data shown.

These figures visualize conditions 1-4 on the NYC data. A full table of results on these measures is available in Table 4.

B.1 Additional results

Corpus	Assistance type	Assistance Model	Task understanding	Task confidence	Understanding of the community	Ability to explain community needs
NYC	No assistance	None	3.33	3.3	3.34	3.31
	Text-based	GPT-4	3.79 **	3.64 **	3.71 **	3.72 **
	Text-based	Llama	3.83	3.80	3.85 **	3.86 **
	Text-based, AI disclosed	GPT-4	3.84 **	3.70 **	3.75 *	3.73 **
	Pre-filled	GPT-4	3.5	3.5 **	3.51	3.51 **
RTFC	No assistance	None	4.0	3.89	3.87	3.84
	Text-based	GPT-4	4.0	3.96	4.04 **	4.04 **

Table 4: Levels of annotator understanding and confidence by condition. Double stars indicate statistically significant increases over baseline conditions for the corpus (as calculated with a two-sided T-test with Bonferroni correction), and single stars indicate statistically significant increases over baseline conditions that reduce to insignificance with Bonferroni correction.

			GPT ground truth, Llama test		
Top-level label	**Sublabel**	**Prevalence (n)**	**F1**	**Precision**	**Recall**
External motivations	Civic Organizations	25	0.60	0.51	0.84
	Employers	24	0.50	0.81	0.54
	Family & Friends	24	0.52	0.63	0.79
	Health Care Providers	21	0.53	0.55	0.76
	Social & News Media	14	0.32	0.47	0.57
Future visions & Takeaways:	Discussion of post-pandemic future	25	0.73	0.88	0.60
	Reflections on the conversation	4	0.15	0.43	0.75
Intrinsic motivations:	Basing decisions on data	12	0.42	0.50	0.75
	Getting back to normal	13	0.38	0.64	0.69
	Not wanting to get the virus	58	0.48	0.78	0.69
Personal COVID experience:	Resilience, Connection, & Hope	20	0.32	0.47	0.35
	Stress, Fear, & Uncertainty	55	0.66	0.65	0.80
Resources that helped	Significant Impact Resources that helped	33	0.64	0.53	0.82
	Unmet community needs	11	0.42	0.56	0.45
Role of community organizations	Health Education & Support	24	0.20	0.54	0.63
	Incentives	15	0.28	0.48	0.73
	Reducing barriers	22	0.35	0.41	0.59
	Trust, Rapport, & Relationships	18	0.20	0.63	0.67
Vaccine hesitancy	Did not vaccinate	12	0.60	0.86	0.50
	Mistrust or Skepticism	28	0.57	0.88	0.82

Table 5: This table compares GPT-4 and Llama annotations on the NYC corpus to each other, by treating GPT-4 labels as ground truth and scoring Llama annotations against GPT-4. The average F1 score for Llama against the GPT-4 baseline is .62 ($\sigma = .10$), which much higher than either model's comparison to human baseline, discussed in the main body of the paper.

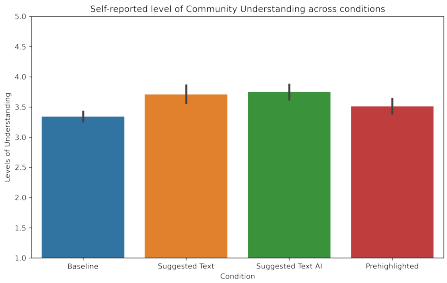

Figure 6: Self-reported understanding of community needs by condition. Conditions 1-4 on NYC data shown.

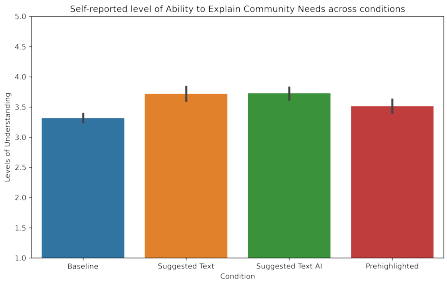

Figure 7: Self-reported ability to explain community needs by condition. Conditions 1-4 on NYC data shown.

C Interface screenshots

Figure 8: *Condition 2*: Text-based label suggestions in interface, with example and label suggestions from RTFC corpus. Annotators could scroll down for more annotations. Interactive tooltips gave extended code definitions, and the full codebook was linked in the header of the annotation task.

Figure 9: *Condition 4:* Pre-highlighted label suggestions in interface, with example and label suggestions from NYC corpus. Interactive tooltip with code definition shown in upper right.

D NYC Conversation Corpus Details

D.1 Conversation guide

The NYC Public Health Corps developed a codebook in partnership with Cortico to elevate concerns from community members during the pandemic period. The main questions asked of participants in each conversation were:

- Opportunities & Challenges of Resourcing
  - What COVID-19 resources have been most helpful for you during the pandemic? And, why?
  - What challenges did you have finding and using resources intended to help you with COVID-19?
- Vaccine Experiences and Decision Making
  - Can you describe a key moment that influenced your decision about the COVID-19 vaccine?
  - Reflecting on this experience you just shared, what information or circumstances helped you make that decision?
- Role of Community Organizations in Community
  - Can you share a story or experience about how the community organizations in your neighborhood supported you and your community during the pandemic?
  - How did those community organizations impact decisions related to COVID-19 vaccinations in your neighborhood?
- Future Resources
  - What will a post-pandemic future look like in your community?
  - How can community organizations help your community thrive in the future?

D.2 NYC Codebook

1. **External motivations** (Theme)
    - **Civic Organizations:** The speaker mentions civic organizations like non-profits, churches, NGOs, and community clubs, associations as a factor in health decisions
        - Example: "My church helped me find alternative childcare during the pandemic."
    - **Family & Friends:** Mentions family and friends as a factor in health decisions
        - Example: "My mom was really opinionated about this from the start. She really wanted us to get the vaccine. She even helped drive us to the vaccine clinic because I don't own a car."
    - **Employers** Mentions place of employment as a factor in health decisions, including employer providing resources or opportunities for vaccination, or co-workers setting a model of vaccine behavior as a factor in health decisions
        - Example: "My job offered drop-in vaccine clinics, which was helpful since the regular clinic hours happen during my work hours."
    - **Social & News Media:** Mentions social media or news media as a factor in health decisions, including Facebook, Twitter, etc. Traditional network, local news, newspapers, or print media that is online
        - Example: "A lot of my friends were posting on Facebook about the vaccine having a chip. That made me nervous."
    - **Health Care Providers:** Mentions healthcare providers as a factor in health decisions, including doctors or nurses
        - Example: "My doctor gave me some information, but I don't trust that the information was up to date and I still don't want the vaccine. So no I haven't gotten it."

2. **Intrinsic Motivations** (Theme)
    - **Fear of Virus:** Mentions not wanting to become ill from COVID as a factor in health decisions
        - Example: "My church helped me find alternative childcare during the pandemic."
    - **Getting Back to Normal:** Mentions a desire for a return to activities and social routines as a factor in health decisions
        - Example: "I thought you know what, if this can help us just keep the kids in school then I'll get the vaccine even if I hate it."
    - **Basing decisions on data:** Mentions considering data, research, or evidence when choosing to get vaccinated
        - Example: "I was seeing these studies show that there is an increased chance of heart problems after the vaccine. So I did not want to get it because I have heart issues in my family."

3. **Role of Community Organizations** (Theme)
    - **Health Education & Support:** Mentions that community health educators were a factor in health decisions
        - Example: "A community health person came to my school and explained what was going on in the pandemic and the latest research on masking. So that's when we started masking."
    - **Support Incentives:** Mentions that a community-based organization provided an incentive or resource in some material form to support during the pandemic. For example, CBO (community-based organization) providing masks, hand sanitizer, gift cards, vaccination opportunities to community members.
        - Example: "My local food pantry gave out masks which was super helpful when they were sold out online."
    - **Trust, rapport, & relationships:** Mentions trust in community organization due to outreach, sharing personal stories, having open conversations, positive relationship-building

  - Example: "It just made us feel like there was somewhere to turn to when everything was chaotic. The church gave us a place to talk about these things and feel safe."
- **Reducing barriers:** Mentions a barrier, struggle, or challenge to implementing their health decisions or asserting agency in health decisions
  - Example: "I just did not feel listened to by my doctor. And there was no alternative to what they were telling me. So"

4. **Resources** (Theme)
   - **Significant Impact Resources:** Mentions that impact resources like food, financial assistance, rent moratorium, student loan suspension, employment helped during COVID
     - Example: "We would have been so lost without the food bank that restocked each week."
   - **Unmet community needs:** Mentions that a resource is needed
     - Example: "We just never found the childcare we needed so that I could keep my job. I haven't worked since 2020."

5. **Vaccine Hesitancy** (Theme)
   - **Did not vaccinate:** Mentions that the speaker did not choose to vaccinate
     - Example: "I just couldn't get over how scary it was that my sister had this reaction to the vaccine. I know it could happen to me. So no I did not go through with the vaccine."
   - **Mistrust or Skepticism:** Mentions that the speaker has/had mistrust or skepticism of the vaccine
     - Example: "There are people telling me this vaccine has a chip in it. I don't want a chip and I just have no way of knowing."

6. **Personal COVID-19 Experience** (Theme)
   - **Resilience, Connection, & Hope:** Mentions agency, control, or feeling empowered during the pandemic period
     - Example: "Helping at my church made me feel like I was making a difference even though the world was going crazy."
   - **Stress, Fear, & Uncertainty:** Mentions stress, fear, or uncertainty during the pandemic period
     - Example: "It was just anxiety all day every day thinking about my kid getting sick at school and bringing it back to her brother at home."

7. **Future Visions & Takeaways**
   - **Conversation Reflections:** Mentions reflections on the conversation
     - Example: "Talking about this has made me remember how hard that period was for our family."
   - **Post-pandemic future:** Mentions a future vision for their life or community after the pandemic
     - Example: "I just can't wait for the schools to go back to normal and I hope we can all learn something from this."

E RTFC Conversation Corpus Details

E.1 RTFC Conversation guide

- Sharing Questions & Lived Experiences
  - As we shed the restrictions of the pandemic, it will be easy for us to lose sight of what we have learned about inequality in America and Boston and how our lived experiences have shaped that learning. Keeping this in mind, I'd like to invite you to think: "What's your question about the future of Boston and your place in that future?"

  - Thank you for sharing your questions with us. Now I'd like to invite you to think, what experience in your life got you to this question?

- Connecting Our Experiences
  - Find someone whose question or experience resonates with your own life. Then I want you to speak to that person and tell them why their question or experience resonated with you and share the story from your life that connects you with their experience.

- Drawing Connections
  - Let's talk a little about what we are hearing. What are you hearing in people's experiences?

- Wrap up
  - Do you have any closing thoughts that you'd like to share or other general reflections? Do you have any questions for us?

E.2 RTFC Codebook

1. **Government and Institutions** (Theme)
   - **Expectations** References to the expectations and aspirations that the public has of elected officials, city government, and/or civic institutions.
   - **Processes:** References to processes through which the public interfaces with government, such as voting, community engagement, campaigning, electoral processes, and other decision-making processes. This may include feelings of exclusion, silencing, or neglect in public meetings; community dynamics within a public meeting; curiosity about electoral results; a lack of confidence in voting as a form of democratic participation.
   - **Accountability:** Statements about the accountability of elected officials, city government, and/or civic institutions to the promises they make and the expectations they set for the public. This may include references to elected officials who "will tell you anything just to get your vote"; the city's failure to address pressing issues, like Mass and Cass; and general questions/doubts about how much the city listens to its residents and factors resident perspectives into decisions. E.g. "You said you were going to do this, and you have/but you haven't yet"
   - **Institutional Resources:** Statements about how people are having difficulty (or success) accessing services provided by government agencies and other institutions that improve one's quality of life. This could include mentions of services and resources like such as housing subsidies, senior services, mental health services, or municipal services like fixing potholes. This could also include statements about the difficulties people face in accessing these services or navigating institutions to get the services and resources they need.
   - **Community Resources:** Statements about how people are leveraging resources in their communities to fulfill their needs and improve one's quality of life. This could include mentions of community-based organizations that fulfill community needs; civic associations; or neighbors that provide support to other neighbors.

2. **Public Health** (Theme)
   - **Mental Health:** Those who struggle with mental health; systemic issues of mental health; responses to those with mental health issues; resources and isntitutions that support mental health
   - **Drugs and Drug Use Disorder:** Addiction, systemic issues of drug use, responses to those with drug use disorders, the culture and environment around drug use
   - **Trauma:** Individual, community, generational traumas. The responses and resources intended to support healing from those traumas. Things that further cause traumas.

- **Quality and Affordable Healthcare:** The accessibility, affordability, and quality of healthcare and other health services.
- **Food Insecurity:** Food access, quality of food accessible, food deserts, affordability of food, systems to support food accessibility.
- **COVID-19:** COVID-19, vaccines, mask, COVID tests, boosters, and the impacts of COVID-19 such as working from home, school closures, and jobs lost.

3. **Safety** (Theme)
    - **Sense of Safety:** Refers to feeling unsafe within daily life routines at home, in one's neighborhood, and throughout the city.
    - **Street Violence:** Refers to situations like street fighting, assaults on the street, unintentional harm of bystanders, etc.
    - **Gun Violence:** Loss of family members due to a shooting, witnessing a shooting AND not limited to gang violence.
    - **Policing:** Refers to being targeted by police (profiled) in certain areas and the lack of policing happening due to neighborhood location, race and/or ethnicity.
    - **Racialized Violence:** Refers to verbal, emotional and physical assaults based on color of skin, race, ethnicity, language.
4. **Infrastructure** (Theme)
    - **Climate Impacts:** Climate change, impact of climate change on the community, actions to address climate change, fears around climate change.
    - **Transportation:** Public transportation like the buses and trains, quality of transportation, affordability and accessibility of transportation, safety of public transit.
5. **Housing** (Theme)
    - **Gentrification and displacement:** Displacement of lower income residents; physical transformation and change of the cultural character of the neighborhood.
    - **Housing Instability:** Difficulty paying rent, having frequent moves, living in overcrowded conditions, or doubling up with friends and relatives.
    - **Homeownership:** Challenges for owning a house; obstacles toward home ownership; expressing the with hope to be a home owner.
    - **Housing quality:** the physical condition of a person's home as well as the quality of the social and physical environment in which the home is located
    - **Housing affordability:** Cost of housing and how affordable that cost is to residents, regardless of tenure (tenant/owner), subsidy (e.g. workforce housing, public housing)
6. **Community Life** (Theme)
    - **Community Relationships:** Relationships between community members, across generations, and across communities. Quality and nature of those relationships.
    - **Community Values:** Values instilled throughout the community, values differences within and across communities.
7. **Education** (Theme)
    - **Quality of Education:** Education that leads to empowerment as a process of strengthening individuals and communities to get more control over their own situations and environments; education systems that focus on the importance of quality learners, quality learning environment, quality content, quality processes, and quality outcomes
    - **School Infrastructure:** Suitable spaces to learn; also spaces that have the infrastructure to address the COVID-19 public health emergency.

- **Life Skills:**The abilities (or the lack of) for adaptive and positive behaviour that enable individuals to deal effectively with the demands and challenges of everyday life in their communities and the world.
- **Youth Spaces:**Available and accessible physical and virtual spaces for activities especially offered to young people to advance their cognitive, emotional, social, and creative skills
- **Higher Education:** Post-secondary academic institutions, including colleges/universities/vocational schools, where individuals engage in advanced learning and research. Could be used to define relationships between students, teachers, administration.

8. **Economic Opportunity** (Theme)

    - **Jobs:** References to a person's ability to provide for themselves and their families. Can include statements about working multiple jobs; working in a particular industry; facing unemployment; job satisfaction; difficulties in finding a job; observations about the job market; discrimination within a job or during a job search; efforts to attain more training or education in order to improve one's job prospects
    - **Economic Assistance:** References to one's ability to access economic supports that enable wealth-building, financial stability, and/or economic growth. This can include statements about individuals (such as one's ability to access home loans) and small businesses (such as a business's ability to access lines of credit).
    - **Income:** Explicit references to income/wages and wealth. This can include discussions about: one's personal income; satisfaction with their income; in/ability to increase their income; in/ability to build wealth; income inequality; the income/wage levels to be able to afford the cost of living in Boston.
    - **Affordable Childcare:** References to one's ability to afford childcare. This is included in Economic Opportunity because childcare affects one's ability to maintain stable employment.
    - **Financial Literacy:** References to people's level of financial literacy, from everyday money management, to processes for applying loans and credit. This can also refer to people's general lack of financial literacy.

9. **Inequality** (Theme)

    - **Race:** RDefined as lack of jobs, services, goods, based on skin color, ethnicity, language.
    - **Class:** Refers to socio economic status, education, and types of disparities, including neighbors re-entering society.
    - **Gender:** Discrimination based on (anatomy) female, male.
    - **Sexual Orientation:** Refers to sexual identity and preference.
    - **Ability:** Refers to disabilities, physical and intellectual.
    - **Immigration Status:** Foreign born, regardless of documentation - this example speaks more to being an immigrant in which English is the second language, which is the barrier of an immigrant.

E.3 Prompts to GPT-4 and Llama

We provided an instruction, list of labels and definitions in the codebook in JSON format for each corpus' codebook. We requested output in JSON format as follows:

```
Your job is to provide a comprehensive set of
    thematic labels for the given quote.
You are given 7 [9] thematic tagging questions,
    subthemes, and general descriptions\\ in the
     JSON below.
Choose ONLY from the tags provided here.

"annotation_schemes": [<list of top-level labels
     and sublabels, in JSON format, with
    definitions>]

For the given conversation quote, return all
    subtags that apply in a single JSON array in
     this format, (or return ‘‘None of the above
    ::I confirm that none of the themes apply"
    if none apply or if the statement is too
    ambiguous to determine):

Expected format:
‘‘‘json
[
  {{
    "highlight_id": highlight_id,
    "tags": ["External Motivations::Employers",
     "Intrinsic Motivations::Not wanting to get
     the virus"]
  }}
]
‘‘‘
Please share this output format with no any
    additional characters, annotations, line
    breaks, or comments.

highlight_id: [id for excerpt]
Conversation quote: [quote]
JSON:
```

Full prompts and code will be included in published Github repo upon publication. The models were prompted at a temperature of 0. Overall, responses were very well-formed according to this prompt, both for Llama and GPT-4. One single label that was not in our codebook was hallucinated 3 times across the generation process for the NYC corpus: *External Motivations: Government*. Qualitatively, we note with interest that this theme did come up often in the conversation quotes, and therefore could be seen as a thematically relevant code despite the violation of instructions needed to produce it. Two labels were hallucinated in the RTFC codebook: "Community Life: Community Resources" and "Housing: Housing Stability." Both of these were also plausible given the conversation content, and were hallucinated just once. All hallucinated labels were removed to ensure fidelity to the original codebook. In one instance, GPT generated "None of the above" in addition to another valid label. For this case, we removed the nonsensical "None of the above" label from the suggested labels. In one case, GPT-4 failed to produce a label of the requested format for the RTFC data. We converted this suggested label into "None of the above" for consistency with the rest of the corpus.

F Crowdworker recruitment

Crowdworkers were recruited from Prolific, and had the following characteristics: located in the US or UK, with English as a first language, with 95-100 percent approval ratings, who had attended some or more college to participate in our annotation experiment. We paid the recommended rate on Prolific of $12/hour, 1.6x the US minimum, and adjusted upward to $12/hour if our initial estimated time was not sufficient to pay workers this amount.

F.1 Annotator "understanding" questions

From the round of IRR validation done before the main round of experiments, we found several examples of very high agreement quote-label pairs. We selected four of them to act as test questions for annotators. Two examples of these high-confidence test questions for the NYC: corpus are listed here.

- High agreement example of *Family & Friends* label: "Right, but you know what? I encouraged my sons and my daughter to vaccinate their kids because you don't know that COVID is new. You don't know how it's going to affect them and the children, my grandkids."
- High agreement example of *Support Incentives:* "I think when I made my decision it came in handy, because I think it was a month before my daughter was starting school and they were giving you $100 for the vaccine. And honestly, that came at a good time. Why? Because I said, 'Okay, they gave me $100. They gave her $100.' And I said, 'Oh, this is good because now I could get you this and that before school starts.' So that was pretty good. I mean, that was nice."

F.2 Instructions to annotators

Following a consent page, annotators received the following instructions:

"First, we need to explain the task we are asking you to complete. We will ask you to read a quotation from a conversation. The conversation is about

<resources and challenges during the COVID-19 pandemic in the United States. Conversations were hosted to better understand resources that helped during the pandemic, challenges to access, and motivations for making health-related decisions during the pandemic>.

We are asking you to identify <7> phenomena in this annotation. Please read about each type before moving forward by going here: [link to Codebook Training Document]. We will check that you have spent at least 3 minutes reading this document before advancing to the task.

There are 15-22 annotations in the task. Review your answer for each question before proceeding."

Then, annotators were given the following choices: *"I agree to read carefully and spend enough time on each annotation"* or *"I do not wish to partake"*. At the bottom, text read *"At the top of the next page, there will be a quote. To annotate, select the check boxes that apply."* In the LLM assistance conditions, this text read: *"At the top of the next page, there will be a quote, followed by a list of suggested labels for the quote. Please read the quote and the list suggested labels, which you may use to assist your annotation. To annotate, select the check boxes that apply."* If they had selected the option to proceed with the study, stimuli to annotate were next presented. After 20 annotations + 2 test questions were presented, participants were given the option to provide demographic information for research purposes.

The crowdworker study was reviewed by our IRB review board, and determined exempt.

G AI Assistance

In this work, the authors used some AI tools to find related works, including Elicit and ScholarQA. Citations were followed and checked. We also used Github Copilot and Cursor for coding assistance, and code was reviewed for errors before being run as well as after being run for any potential errors.