

# Leveraging Explicit Reasoning for Inference Integration in Commonsense-Augmented Dialogue Models

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## Abstract

Open-domain dialogue systems need to grasp social commonsense to understand and respond effectively to human users. Commonsense-augmented dialogue models have been proposed that aim to infer commonsense knowledge from dialogue contexts in order to improve response quality. However, existing approaches to commonsense-augmented dialogue rely on implicit reasoning to integrate commonsense inferences during response generation. In this study, we explore the impact of explicit reasoning against implicit reasoning over commonsense for dialogue response generation. Our findings demonstrate that separating commonsense reasoning into explicit steps for generating, selecting, and integrating commonsense into responses leads to better dialogue interactions, improving naturalness, engagement, specificity, and overall quality. Subsequent analyses of these findings unveil insights into the effectiveness of various types of commonsense in generating responses and the particular response traits enhanced through explicit reasoning for commonsense integration. Our work advances research in open-domain dialogue by achieving a new state-of-the-art in commonsense-augmented response generation.

## 1 Introduction

In open-domain dialogue, dialogue systems must engage in open-ended conversation with a human user, adapting fluently and intelligently to the topics that are introduced, which often involve discussions about life experiences (Robinson et al., 2008; Fillwock and Traum, 2018; Mitsuda et al., 2019). As illustrated by the dialogue example in Figure 1, meaningful follow-up responses are often driven by speculative thinking regarding the experiences shared by the human user (Finch et al., 2020), such as predictions about likely future plans of the user ([b], Turn 2) and likely reasons behind the user’s actions ([d], Turn 4). This manner of inferential

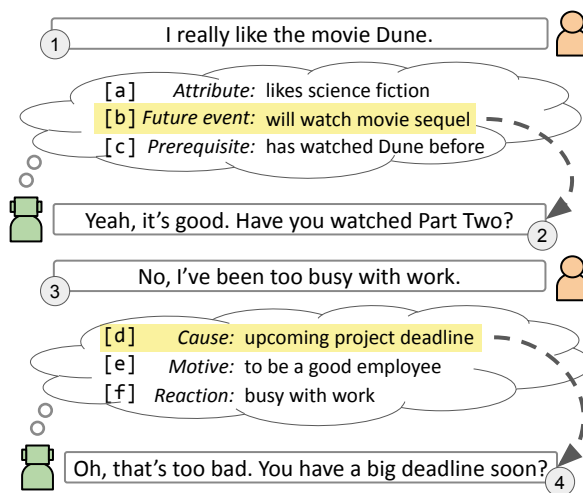


Figure 1: Example dialogue demonstrating the reasoning flow for integrating commonsense.

reasoning enriches the contextual understanding of the user’s input and facilitates the generation of insightful responses. The ability to draw such inferences stems from shared worldviews and mutual experiences of humans—a phenomenon commonly known as “commonsense” (Clark, 1991).

As such, the goal of commonsense-augmented dialogue modeling is to leverage useful commonsense inferences for producing more compelling and human-like responses in human-computer dialogue. For a given dialogue situation, there are numerous commonsense inferences that can be drawn since inferential commonsense has a many-to-many mapping due to its speculative nature (Shen et al., 2022; Finch and Choi, 2024). Consequently, commonsense-augmented dialogue modeling is a reasoning process of (1) deriving commonsense knowledge that likely holds true for a given dialogue context, (2) identifying a subset of true commonsense that is appropriate for generating a response, and (3) synthesizing a response from the identified commonsense knowledge. No previous work tackles all three of these components of commonsense-augmented dialogue modeling in

an explicit manner. Often, the identification of appropriate commonsense for response generation is tackled jointly with response generation itself, where a generative model’s attention mechanisms implicitly learn which commonsense knowledge is most relevant to generating a response in each dialogue context (Zhang et al., 2020; Sabour et al., 2022; Liu and Kilicoglu, 2023). However, recent work in a variety of text generation tasks, including dialogue modeling, suggests that breaking down a model into a sequence of explicit reasoning steps improves the correctness and overall quality of model outputs (Wei et al., 2022; Chae et al., 2023; Lee et al., 2023)

Inspired by this, we hypothesize that dialogue modeling that modularizes commonsense reasoning into explicit steps will lead to more compelling dialogue responses. To explore this, we leverage Large Language Models (LLMs) to perform explicit commonsense reasoning for commonsense-augmented response generation since LLM-based approaches to dialogue have achieved remarkable success (Lee et al., 2022; Kim et al., 2022; Chen et al., 2023). Our approach first generates multiple commonsense inferences for a dialogue context, covering several different social commonsense types. Since commonsense inferences can be produced that are true for a dialogue context but not useful for generating an appropriate response, a subset of the generated inferences are then explicitly selected based on their relevance to response generation. Finally, a response generator model produces a response for the dialogue context that integrates the selected commonsense.

We find strong evidence that explicit reasoning over commonsense inferences leads to better dialogue interactions, improving the naturalness, engagingness, specificity, and overall quality of the responses against several alternative strategies for dialogue response generation. Further analysis provides insights on which types of commonsense are most useful for response generation, revealing that predictions of personal characteristics and likely future events lead to the most favorable outcomes. Moreover, we assess human-provided explanations of response quality to identify the key response attributes that shape human perception of response quality and the particular response traits enhanced through commonsense integration. Taken together, our results demonstrate that isolating commonsense reasoning into explicit reasoning steps improves several aspects of response quality, achieving a

new state-of-the-art in commonsense-augmented dialogue modeling. We make all code, models, and data publicly available to facilitate future work.<sup>1</sup>

## 2 Related Work

Typical approaches to commonsense-augmented response generation include two steps, where a commonsense model first produces a set of commonsense inferences for a given dialogue context and then provides the inferences in conjunction with the dialogue context to a response generator model. Commonsense inference has been modeled as a retrieval process from a static commonsense knowledge base (Zhou et al., 2018; Zhang et al., 2020; Wu et al., 2020; Zhong et al., 2021; Huang et al., 2022; Wu et al., 2022a; Li et al., 2022; Wu et al., 2022b; Varshney et al., 2022; Li et al., 2023) such as ConceptNet (Speer et al., 2017) or using a commonsense generator that can produce novel commonsense inferences for a given context (Tu et al., 2022; Sabour et al., 2022; Fu et al., 2023; Liu and Kilicoglu, 2023) such as COMET-ATOMIC (Bosselut et al., 2019). A limitation of these approaches is that the commonsense models focus on producing commonsense candidates that are true, regardless of their downstream appropriateness for response generation. Consequently, the response generator model must perform implicit commonsense reasoning to select which commonsense candidates should be integrated into the response. By contrast, our work hypothesizes that explicitly modeling which commonsense is appropriate to integrate into a response, independently of response generation, is a better strategy for augmenting a model with commonsense.

An alternative direction for commonsense-augmented response generation focuses on training a specialized commonsense generator with the goal of outputting only the commonsense which is relevant for generating responses in a given dialogue context. Some works accomplish this by training a single model to sequentially produce relevant commonsense for a dialogue context followed by a response that incorporates it (Liu et al., 2022; Zhou et al., 2022a,b) whereas others train a specialized commonsense generative model to generate chain-of-thought sequences of commonsense inferences which are then used as input for response generation by LLMs (Chae et al., 2023). A possible limitation of these specialized commonsense generators

<sup>1</sup><https://github.com/anonymous>

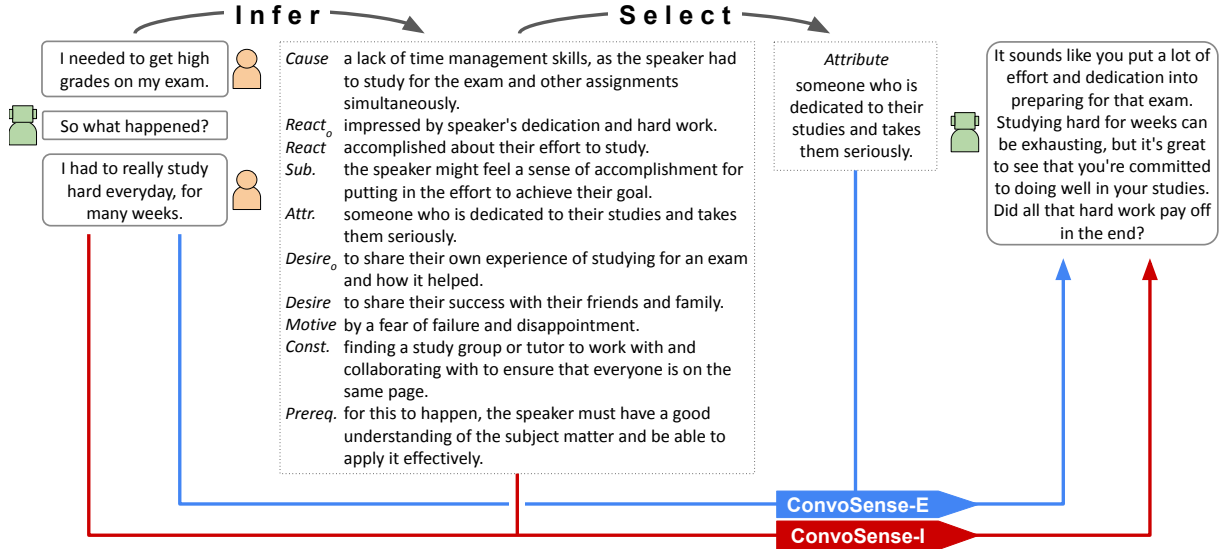


Figure 2: Overview of the explicit and implicit reasoning approaches (ConvoSense-E/I).

is that they jointly tackle two important reasoning steps together: determining true commonsense for a given dialogue situation and deciding on the relevance of specific commonsense for response generation. Our approach instead models these two steps explicitly using separate components.

In summary, our work is the first to distinguish three explicit reasoning steps for commonsense-augmented response generation. Our method fully separates the tasks of commonsense generation, commonsense selection, and response generation, representing the most explicit approach for modeling dialogue commonsense to date.

### 3 Response Generation via Explicit vs. Implicit Reasoning

To explore the impact of explicit reasoning over commonsense inferences against the typically utilized implicit reasoning approach, we develop two prompt-based LLM strategies for response generation that treat generated inferences as speculative thoughts to guide follow-up response generation. These two approaches utilize the same inference generation procedure and differ on the strategy for integrating commonsense inferences into a follow-up response. The implicit reasoning variant provides all commonsense inferences as input to an LLM which is prompted to consider the inferences when generating the best follow-up response, similar to previous works. The explicit reasoning variant involves a three-step generate-select-and-respond procedure, using LLM prompting to explicitly identify the best commonsense inferences and subsequently synthesize them into a follow-

up response. We first discuss the shared Inference Generation module (§3.1), before detailing the implicit reasoning (§3.2) and the explicit reasoning approaches (§3.3). Figure 2 presents an overview of the approaches.

#### 3.1 Inference Generation

The first step of both approaches is to identify multiple social commonsense inferences that are likely true for a given dialogue context.

**Inference Source** To dynamically generate inferences relevant to a dialogue context, we use a generative model of social commonsense tailored for dialogue. Our aim is to produce individual inferences, which are reasonable to the dialogue context, are predictive in nature to the dialogue situation, and cover a wide variety of commonsense types. We adopt the ConvoSenseGenerator from Finch and Choi (2024), a T5-based model trained on the ConvoSense dataset to output inferences for a provided dialogue context and commonsense type. ConvoSenseGenerator excels in producing commonsense inferences across 10 different social commonsense types, surpassing existing works of ComFact (Gao et al., 2022), Reflect (Zhou et al., 2022a), and CICERO (Ghosal et al., 2022; Shen et al., 2022) in type coverage as well as the reasonableness and predictiveness of the generated inferences. Furthermore, ConvoSenseGenerator allows precise control over the type of inferences generated, unlike the model proposed by Chae et al. (2023) which outputs a set of three inferences with no explicit control over the outputted types.

**Inference Distribution** 10 commonsense inferences are outputted for a provided dialogue context, each corresponding to one of the 10 commonsense types covered by ConvoSenseGenerator (Table 1). Initially, we explored outputting the top-ranked inference from beam search for each type but found significant semantic overlap in the inferences outputted across types. Since semantically unique inferences are critical for studying the impact of reasoning over these inferences, we implement a diverse beam search approach (Vijayakumar et al., 2016) to output five inferences per type and then select one inference per type such that between-type cosine similarity of SBERT inference embeddings (Reimers and Gurevych, 2019) is minimized, following the results in Finch and Choi (2024) that show diverse beam search helps to increase inference uniqueness.

Type	Prefix
Cause	I think it is possible the previous dialogue turn was caused by
React <sub>o</sub>	The Listener (You) feels
React	I think the Speaker (Other) feels
Subsequent	Next, I predict
Attribute	I think the Speaker (Other) is
Desire <sub>o</sub>	The Listener (You) wants
Desire	I think the Speaker (Other) wants
Motivation	I think the Speaker (Other) is motivated
Constituent	I think it is possible the previous dialogue turn depends on
Prerequisite	I think it is possible the previous dialogue turn requires

Table 1: Prefixes used for the commonsense inferences.

**Inference Representation** Inferences generated by ConvoSenseGenerator are augmented with natural language prefixes, transforming them into complete sentences. These prefixes serve to indicate the level of speculation inherent in the predictions. Inferences pertaining directly to the conversational role played by the system are treated as factual, while those concerning the other interlocutor in the conversation or the dialogue situation itself are considered speculative. Table 1 provides the ten inference types and their corresponding prefixes.

### 3.2 Implicit Reasoning

Given the output from inference generation, the implicit reasoning approach immediately performs response generation by taking all generated inferences as input. Table 6 provides the prompt for this approach (Appx. A), referred to as ConvoSense-I.

**Response Generation** The Response Generation module takes as input the set of generated inferences and the dialogue context, and outputs the next response. We use GPT-3.5 for response generation, which is instructed to carefully consider all of the commonsense inferences and then write the best response based on this consideration. This produces a dialogue response that is grounded on implicitly selected commonsense inferences.

### 3.3 Explicit Reasoning

Given the output from inference generation, the explicit reasoning approach performs inference selection over the generated inferences before composing the follow-up response by expressing the selected inferences. Table 5 provides the prompts for this approach (Appx. A), referred to as ConvoSense-E.

**Inference Selection** The goal of inference selection is to identify which inferences are most useful towards generating an interesting and appropriate response to the dialogue context. GPT-3.5 is tasked with selecting  $k$  inferences from the full set of inferences by being prompted to carefully consider each inference and strategically determine which inferences are the most useful, relevant, and interesting for the next response in the dialogue context. The selected inferences are outputted as a list.

The determination of the number  $k$  of inferences to select is treated as a hyperparameter to be optimized. In pilot studies, we observed that  $k = 1$  performed best, since increasing  $k$  often resulted in longwinded, unfocused responses that integrated too many disparate commonsense inferences.

**Response Generation** After inference selection, response generation takes as input the list of selected inferences and the dialogue context, and outputs the next response. GPT-3.5 is instructed to synthesize the semantic content provided in the selected inferences into an engaging and appropriate response, producing a dialogue response grounded on explicitly selected commonsense inferences.

### 3.4 Prompt Formatting

For all GPT prompts, the dialogue context is provided as a sequence of turns, prefixed with speaker labels. Few-shot examples are also provided to both ConvoSense-E and ConvoSense-I. For ConvoSense-E, we construct 10 inference selection examples, one for each inference type included in this study, and 100 response generation



examples, 10 for each inference type. During inference, the 10 inference selection examples are used in the inference selection prompt. Once an inference is selected from inference selection, then the response generation examples corresponding to its type are used in the response generation prompt (Table 5; Appx. A). For ConvoSense-I, we choose 10 response generation examples from those crafted for ConvoSense-E, ensuring one example for each commonsense type. During inference, these 10 response generation examples are used in the response generation prompt (Table 6; Appx. A).

## 4 Experiments

To study the impact of explicit reasoning over commonsense inferences on response generation, we compare ConvoSense-E against three alternative approaches, two which utilize implicit reasoning over commonsense (ConvoSense-I and Doctor) and one which does not have access to external commonsense resources (GPT).

**ConvoSense-I** represents the implicit reasoning approach that is a direct comparison against ConvoSense-E (Section 3.2).

**Doctor** is the state-of-the-art for commonsense-augmented dialogue. It uses an implicit reasoning approach in which a trained commonsense model generates a subset of commonsense types for a given dialogue context that are then provided to GPT-3.5 for response generation. We use the released model and prompt from Chae et al. (2023).

**GPT** is a baseline model representing the capability of GPT-3.5 for dialogue response generation without any direct integration of commonsense. The prompt is shown in Table 7 (Appx. A).

For fair comparison, we employ the same GPT-3.5 version in each approach, choosing the latest version at the time of writing (gpt-3.5-turbo-0125) with a temperature of 0.7.

### 4.1 Test Data

To conduct a realistic evaluation of the approaches under study, the test data consists of dialogues sampled from an “out-of-distribution” dataset for all models: Reflect (Zhou et al., 2022a). The Reflect dataset is composed of human-written dialogues that are based on descriptions of everyday situations. Table 8 (Appx. B) presents examples of the response outputs from each model.

## 4.2 Evaluation

We perform pairwise preference selections between pairs of dialogue approaches, where responses from two different dialogue approaches for the same dialogue context are shown to human judges who are instructed to identify which response better satisfies the indicated characteristic. Following the improvements in dialogue characteristics from earlier commonsense-augmented dialogue works (Zhou et al., 2022a; Chae et al., 2023), we evaluate based on the following four criteria:

**Natural:** Which response is more natural (human-like) as the next response in the dialogue?

**Engaging:** Which response is more engaging and interesting as the next response in the dialogue?

**Specific:** Which response contains content that is more specific and unique to the shown dialogue?

**Quality:** Which response demonstrates better overall quality as the next response in the dialogue?

Human judges are also instructed to provide a freeform text explanation of their reasoning behind which response had the better quality. 100 dialogues are sampled from the test data for use in the evaluations. Three Amazon Mechanical Turkers perform each evaluation task and are paid \$0.15 USD per task. The annotators achieve moderate inter-annotator agreement, with Krippendorff’s alpha scores of 0.442, 0.560, 0.595, and 0.561 for naturalness, engagingness, specificity, and quality, respectively. The worker screening criteria and evaluation interface are provided in Appendix C.

## 4.3 Results

	Natural	Engaging	Specific	Quality
ConvoSense-E	<b>82.7</b>	<b>92.3</b>	<b>91.3</b>	<b>92.0</b>
Doctor	17.3	7.7	8.7	8.0
ConvoSense-E	<b>75.7</b>	<b>82.7</b>	<b>86.3</b>	<b>84.3</b>
GPT	24.3	17.3	13.7	15.7
ConvoSense-E	<u>55.3</u>	<b>66.7</b>	<b>63.7</b>	<b>63.7</b>
ConvoSense-I	44.7	33.3	36.3	36.3
ConvoSense-I	<b>84.7</b>	<b>89.3</b>	<b>86.3</b>	<b>89.7</b>
Doctor	15.3	10.7	12.7	10.3
ConvoSense-I	<b>68.7</b>	<b>67.7</b>	<b>73.0</b>	<b>70.3</b>
GPT	31.3	32.3	27.0	29.7

Table 2: Pairwise evaluation results showing the preference percentages. Winning models in each comparison are statistically significant for all characteristics, except where underlined (proportion test,  $\alpha < 0.01$ ).

Table 2 shows the preference results for the models under study. It is clear from the results that ConvoSense-E outperforms the alternative approaches in generating natural, engaging, and specific responses which are overall preferred as next responses in dialogue. The preference for ConvoSense-E is particularly pronounced regarding engagingness, specificity, and overall response quality. The preference for ConvoSense-E is less dramatic for response naturalness, especially against ConvoSense-I, although ConvoSense-E still maintains a slight advantage.

ConvoSense-I is found to be the most competitive approach to ConvoSense-E, with the highest rate of preference wins relative to the alternative approaches. This is further corroborated by direct pairwise comparisons between ConvoSense-I and each of the alternative approaches, Doctor and GPT. The results show that ConvoSense-I outperforms both Doctor and GPT, although the preference is not as strong as that for ConvoSense-E.

We also find that GPT responses are more competitive with responses from ConvoSense-E than Doctor responses, as indicated by the rate of ConvoSense-E wins being lower against GPT than against Doctor. Interestingly, this suggests that the previous commonsense-augmented dialogue model is producing responses that are worse than GPT. We discuss this further in Section 5.5.

## 5 Discussion

### 5.1 Impact of Explicit Reasoning

The results in Table 2 overwhelmingly indicate that explicit reasoning over dialogue-relevant commonsense inferences results in more appealing responses to human judges. The proposed approach to dialogue modeling that decomposes response generation into separate reasoning and integration steps is quite advantageous. In this era of leveraging powerful LLMs to perform tasks with little-to-no direct training, work like that in this study is revealing that modularized generation strategies are superceding the end-to-end modeling paradigms that have dominated in the past.

Of all of the dialogue characteristics under study, the naturalness of the follow-up response is least affected by the choice of commonsense reasoning strategy. When directly comparing explicit to implicit reasoning over the same commonsense inferences, as elucidated by the pairwise selections between ConvoSense-E and ConvoSense-I, there

is not a strong difference with regard to response naturalness. This suggests that, although explicit reasoning aids in the engagingness and specificity of the response to its dialogue context, it is not as useful towards improving how natural the response is for the dialogue.

Furthermore, it can be seen that there is a large preference for responses from both ConvoSense-E and ConvoSense-I when compared to GPT responses. This result indicates that augmenting responses with commonsense improves on the native response generation of GPT, regardless of integration strategy (explicit vs. implicit).

### 5.2 Impact of Commonsense Source

As discussed in Section 3.1, there are several sources for commonsense for dialogue. Through the experiments in this study, we are able to compare the downstream utility of two of these sources: that used in Doctor, which has been shown to lead to better response outcomes than the resources that came before it, and ConvoSense, which has not been applied to response generation before this study. Specifically, the pairwise selection between ConvoSense-I and Doctor enables a comparison of the underlying commonsense resources since their main difference is the source of commonsense inferences used in their approaches. The strong preference for ConvoSense-I against Doctor demonstrates the superiority of the ConvoSense inferences for leading to compelling responses in dialogue. This provides evidence that the commonsense resource used in this work advances dialogue modeling beyond the resource used in the previous state-of-the-art model, Doctor.

### 5.3 Impact of Commonsense Type

As indicated in Zhou et al. (2022a), the choice of grounding commonsense type has an impact on the resulting quality of the response for a given dialogue context. To better understand the effect of each commonsense type on response generation in the context of explicit commonsense reasoning, we decompose the pairwise selection results into isolated results for each type of selected commonsense. Figure 3 shows the pairwise selection results between ConvoSense-E and the other approaches, split into groupings of test instances based on the type of commonsense selected by ConvoSense-E.

From these results, it can be seen that responses that integrate Attribute and Subsequent commonsense inferences consistently perform quite

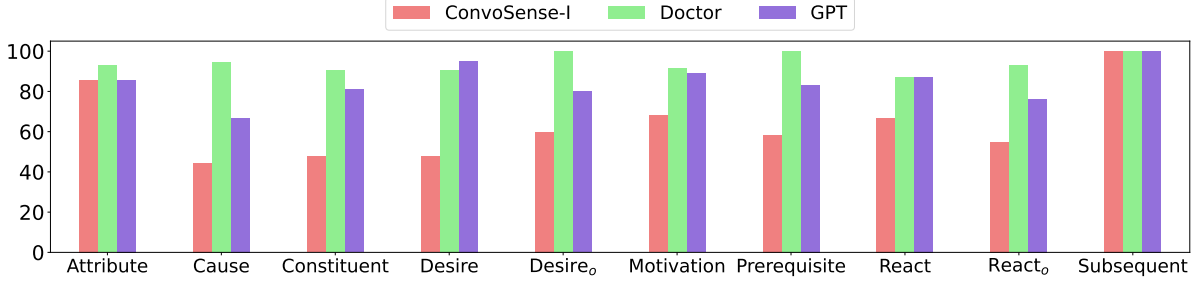


Figure 3: Percentage that ConvoSense-E wins against other models on Quality, split by the type of commonsense selected for response integration by ConvoSense-E.

well against the alternative approaches. On the other hand, responses that integrate Cause, Constituent, Desire, and React<sub>o</sub> inferences seem to perform the worst, especially against ConvoSense-I. These decomposed results reveal potential weaknesses of GPT-3.5 to reasoning and generation on certain commonsense types for response generation (e.g. Cause, Constituent, Desire, and React<sub>o</sub>). The approach used in this work relies on the capability of GPT-3.5 to reason about and synthesize commonsense inferences for response generation given a handful of appropriate few-shot examples. Further work on explicit reasoning processes for commonsense-augmented dialogue should explore improvements to the reasoning process and integration strategies to ensure each commonsense type is utilized optimally.

#### 5.4 Influential Aspects from Human Feedback

Based on the preference results in Table 2, the overall quality preference is more aligned with the judgements on which response is more engaging and specific to the context, and less aligned with the judgements for naturalness. To explore the influential aspects on perceived response quality in greater detail, we examine the textual explanations of overall quality preference provided by the human judges for each of their judgements.

We utilize an automated aspect identification procedure to summarize the human-written explanations into sets of influential characteristics of the preferred response. This aspect identification procedure uses GPT-3.5 to output short phrases (one or two words) that represent each of the indicated characteristics mentioned in the explanation (Table 9; Appx. D). On an example set of 50 explanations with characteristics identified by a human annotator, this procedure obtains 0.82 precision and 0.83 recall of the characteristics.

We run this aspect identification procedure on the explanations collected from the evaluations. We then manually review the outputted individual characteristics and find that there is a high degree of distinct yet synonymous characteristics being outputted. To aggregate the characteristics by synonymous meaning, we construct a mapping between the outputted characteristics to 12 categories. Table 8 (Appx. B) shows examples of the predicted aspects and their corresponding mapped categories. Figure 4 shows the distribution of categories in the explanations for each winning model.

Across all models, there are five characteristics that are most often cited as a determining factor for the identification of a better response: the supportive nature of the response, the level of engaging and interesting information, the specificity of the response contents, the degree of empathy, and the naturalness. This suggests that these characteristics are the most influential aspects contributing to response favorability among human judges.

Specifically for ConvoSense-E, it has a higher rate of explanations that highlight the response specificity, supportiveness, and detailedness as influential features for overall response preference, compared to the other models. This showcases that the ConvoSense-E approach is more capable than the other models at producing specific, supportive, and detailed responses to a provided dialogue context. In addition, it can be seen that both approaches that utilize ConvoSense inferences receive more preference wins due to the empathetic and helpful nature of their responses, suggesting that the commonsense used in these approaches is useful for improving the empathy displayed in the responses and encouraging the responses to be solution/advice-oriented to the events being discussed in the dialogue, more so than that provided by responses from Doctor or native GPT.

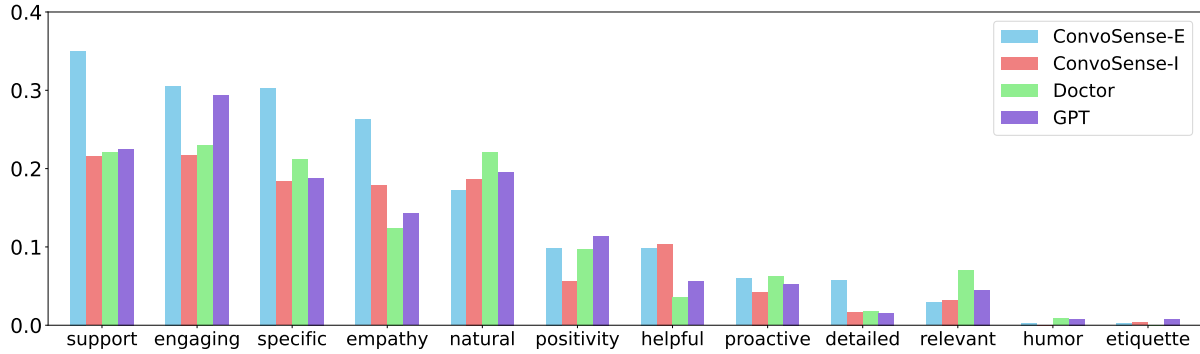


Figure 4: Proportion of explanations that include each response characteristic for each model.

## 5.5 Baseline Prompt Variation

One unexpected outcome of this work is the poor performance of the Doctor approach. As noted in Section 4.2, GPT is more competitive with ConvoSense-E than Doctor in terms of human preference selection on various characteristics. This is contrary to the results presented in Chae et al. (2023), which indicate that Doctor outperforms GPT in terms of naturalness and specificity. To explicitly compare the GPT baseline used in this work against Doctor, we conduct the pairwise preference selection evaluation from Section 4.2 between these two approaches. From the results shown in Table 3, it is confirmed that Doctor is indeed outperformed by our GPT baseline.

	Natural	Engaging	Specific	Quality
GPT	<b>72.0</b>	<b>82.3</b>	<b>77.7</b>	<b>80.7</b>
Doctor	28.0	17.7	22.3	19.3

Table 3: Pairwise evaluation results showing the win percentages. All wins are statistically significant (proportion test,  $\alpha < 0.01$ ).

We hypothesize that we have utilized a stronger GPT baseline in this work than that used in Chae et al. (2023). To verify this hypothesis, we conduct the pairwise preference selection evaluation between responses from the GPT approach from this work and the prompt released by Chae et al. (2023). From the results in Table 4, we are able to confirm that our GPT prompt does indeed lead to stronger responses than that used previously, thus helping to explain the evaluation discrepancies observed in this work. This difference in outcomes between two different GPT prompts highlights the need for careful construction of prompts for using LLM capabilities as baselines, in order to ensure appropriate representation of the power of the LLM

and to avoid an overestimate of the impact of new dialogue approaches. It is also possible that GPT performance has improved in general since the publication of Chae et al. (2023), further emphasizing the need to continue to include such baseline models in follow-up experiments to track performance progression.

	Natural	Engaging	Specific	Quality
GPT	<b>55.0</b>	<b>58.0</b>	<b>57.7</b>	<b>61.3</b>
GPT <sub>chae</sub>	45.0	42.0	42.3	38.7

Table 4: Pairwise evaluation results showing the win percentages. All wins are statistically significant, except where underlined (proportion test,  $\alpha < 0.01$ ).

## 6 Conclusion

The findings of this paper underscore the benefits of an explicit approach for incorporating commonsense into dialogue responses, in which the separate generation, selection, and integration of commonsense into dialogue responses enables improvements in response quality. Our findings not only showcase the efficacy of this explicit reasoning model but also shed light on the types of commonsense most beneficial for response generation and reveal the fine-grained response characteristics that are improved through this explicit reasoning process. By elucidating these advancements and insights, we contribute to the ongoing evolution of dialogue systems, making interactions more engaging, contextually aware, and satisfying for users. We anticipate future research will extend the scope of explicit reasoning in dialogue response generation to encompass a broader range of information sources and alternative reasoning strategies, thus supporting the advancement of tailoring dialogue systems to diverse domains and user populations.



## 7 Limitations

By showcasing the advantage of explicit reasoning steps for commonsense integration into dialogue response generation, the findings of our work provide valuable insights into a fruitful direction for future dialogue works to follow to optimize dialogue performance. To further understand the impact of this explicit reasoning and identify any outstanding challenges, there are a few limitations to be noted in our work that can inform follow-up investigations.

**Generality Beyond GPT-based Systems** Our experiments primarily focused on GPT-3.5-based dialogue systems. Although we attempted to extend our methods to Llama2, we observed poor performance. This suggests that additional work is necessary to implement explicit reasoning to other, less powerful models. Future work should explore the implementation of explicit reasoning for a broader range of models and investigate fine-tuning approaches to enhance performance across different LLMs.

**Strategy of Explicit Reasoning** The explicit reasoning step undertaken in our study involves selecting a single commonsense inference from a large pool of candidates, which will be integrated into the follow-up response. However, there are many alternative reasoning strategies that could be explored. For instance, strategies could be developed to prioritize inferences that address the user’s emotional needs, generate intelligent follow-up questions, or achieve other specific dialogue goals. Investigating these alternative strategies could reveal further enhancements in response quality and user engagement depending on the dialogue application.

**Commonsense Information Source** Our research investigates explicit reasoning specifically in the context of social commonsense inferences. Future work should explore expansion to additional types of commonsense, such as temporal or property-based, to further the investigation of commonsense-augmented dialogue models and the utility of explicit reasoning.

**Static Evaluation** We follow the evaluation paradigm of previous commonsense-augmented dialogue works (Zhou et al., 2022a; Chae et al., 2023) in which a response is generated for a static dialogue context. Although this provides an understanding of the response generation capabilities of dialogue models, real-world deployment of such

systems that involves multi-turn back-and-forth interactions can reveal aspects of dialogue models that are not demonstrated through static evaluations. Future work should explore the deployment of dialogue systems with explicit reasoning over commonsense to further understand their performance with human users.

## 8 Ethical Considerations

**Bias and Stereotyping** One important consideration regarding integrating commonsense reasoning into dialogue response generation is the potential for perpetuating stereotypes due to the generalized nature of commonsense knowledge. This could result in dialogue systems producing responses that reflect these stereotypes or exhibit unfair biases. While we would expect there to be a negative impact on human reception of these responses if they are significantly biased, which is not observed in this study, it is possible that human evaluators share similar stereotypes or biases and therefore do not find these responses uncomfortable. This highlights the importance of future research to thoroughly investigate the risks of bias in commonsense reasoning for response generation, ensuring the development of equitable AI systems.

**Risks of Explicit Dialogue Model Control** Having a dialogue system design that relies on explicit reasoning steps enables the opportunity for antisocial reasoning or response strategies to be directly inserted into a model, which can lead to a higher rate of such behaviors being expressed as compared to indirect learning from training data. At the same time, however, it also affords opportunities to promote strategies that aim to reduce such antisocial response behaviors. This controllable approach contrasts with end-to-end dialogue systems, providing a more precise method for mitigating harmful outputs, which we leave to future work to explore the success of such strategies.

**Compensation of Human Evaluators** We ensure fair compensation for the human evaluators involved in our study, with an estimated hourly pay rate of \$12 USD, which exceeds minimum wage.

## References

Antoine Bosselut, Hannah Rashkin, Maarten Sap, Chaitanya Malaviya, Asli Celikyilmaz, and Yejin Choi. 2019. Comet: Commonsense transformers for automatic knowledge graph construction. In *Proceedings*

728	of the 57th Annual Meeting of the Association for	783
729	Computational Linguistics, pages 4762–4779.	784
730	Hyunjoo Chae, Yongho Song, Kai Ong, Taeyoon	785
731	Kwon, Minjin Kim, Youngjae Yu, Dongha Lee,	786
732	Dongyeop Kang, and Jinyoung Yeo. 2023. <a href="#">Dialogue</a>	787
733	<a href="#">Chain-of-Thought Distillation for Commonsense-</a>	
734	<a href="#">aware Conversational Agents</a> . In <i>Proceedings of the</i>	
735	<i>2023 Conference on Empirical Methods in Natural</i>	
736	<i>Language Processing</i> , pages 5606–5632, Singapore.	
737	Association for Computational Linguistics.	
738	Maximillian Chen, Alexandros Papangelis, Chenyang	
739	Tao, Seokhwan Kim, Andy Rosenbaum, Yang Liu,	
740	Zhou Yu, and Dilek Hakkani-Tur. 2023. Places:	
741	Prompting language models for social conversation	
742	synthesis. In <i>Findings of the Association for Compu-</i>	
743	<i>tational Linguistics: EACL 2023</i> , pages 814–838.	
744	HH Clark. 1991. <a href="#">Grounding in communication</a> . <i>Per-</i>	
745	<i>spectives on Socially Shared Cognition</i> , pages 127–	
746	149.	
747	Sarah Fillwock and David Traum. 2018. <a href="#">Identification</a>	
748	<a href="#">of personal information shared in chat-oriented dia-</a>	
749	<a href="#">logue</a> . In <i>Proceedings of the Eleventh International</i>	
750	<i>Conference on Language Resources and Evaluation</i>	
751	<i>(LREC 2018)</i> .	
752	Sarah E. Finch and Jinho D. Choi. 2024. <a href="#">ConvoSense:</a>	
753	<a href="#">Overcoming Monotonous Commonsense Inferences</a>	
754	<a href="#">for Conversational AI</a> . <i>Transactions of the Associa-</i>	
755	<i>tion for Computational Linguistics</i> , 12:467–483.	
756	Sarah E. Finch, James D. Finch, Ali Ahmadvand, Ingyu,	
757	Choi, Xiangjue Dong, Ruixiang Qi, Harshita Sahi-	
758	jwani, Sergey Volokhin, Zihan Wang, Zihao Wang,	
759	and Jinho D. Choi. 2020. <a href="#">Emora: An Inquisitive</a>	
760	<a href="#">Social Chatbot Who Cares For You</a> . <i>arXiv preprint</i> .	
761	Yahui Fu, Koji Inoue, Chenhui Chu, and Tatsuya Kawa-	
762	hara. 2023. <a href="#">Reasoning before responding: Integrat-</a>	
763	<a href="#">ing commonsense-based causality explanation for</a>	
764	<a href="#">empathetic response generation</a> . In <i>Proceedings</i>	
765	<i>of the 24th Annual Meeting of the Special Interest</i>	
766	<i>Group on Discourse and Dialogue</i> , pages 645–656,	
767	Prague, Czechia. Association for Computational Lin-	
768	guistics.	
769	Silin Gao, Jena D. Hwang, Saya Kanno, Hiromi Wakaki,	
770	Yuki Mitsufuji, and Antoine Bosselut. 2022. <a href="#">Com-</a>	
771	<a href="#">Fact: A Benchmark for Linking Contextual Com-</a>	
772	<a href="#">monsense Knowledge</a> . In <i>Findings of the Associa-</i>	
773	<i>tion for Computational Linguistics: EMNLP 2022</i> ,	
774	pages 1656–1675, Abu Dhabi, United Arab Emirates.	
775	Association for Computational Linguistics.	
776	Deepanway Ghosal, Siqi Shen, Navonil Majumder,	
777	Rada Mihalcea, and Soujanya Poria. 2022. <a href="#">CICERO:</a>	
778	<a href="#">A dataset for contextualized commonsense inference</a>	
779	<a href="#">in dialogues</a> . In <i>Proceedings of the 60th Annual Meet-</i>	
780	<i>ing of the Association for Computational Linguistics</i>	
781	<i>(Volume 1: Long Papers)</i> , pages 5010–5028, Dublin,	
782	Ireland. Association for Computational Linguistics.	
	Yu-Cian Huang, Edwinn Gamborino, Yan-Jia Huang,	
	Xiaobei Qian, Li-Chen Fu, and Su-Ling Yeh. 2022.	
	Inferring stressors from conversation: Towards an	
	emotional support robot companion. <i>International</i>	
	<i>Journal of Social Robotics</i> , 14(7):1657–1671.	
	Hyunwoo Kim, Jack Hessel, Liwei Jiang, Peter West,	
	Ximing Lu, Youngjae Yu, Pei Zhou, Ronan Le Bras,	
	Malihe Alikhani, Gunhee Kim, Maarten Sap, and	
	Yejin Choi. 2022. Soda: Million-scale dialogue dis-	
	tillation with social commonsense contextualization.	
	<i>ArXiv</i> , abs/2212.10465.	
	Gibbeum Lee, Volker Hartmann, Jongho Park, Dimitris	
	Papailiopoulos, and Kangwook Lee. 2023. <a href="#">Prompted</a>	
	<a href="#">llms as chatbot modules for long open-domain con-</a>	
	<a href="#">versation</a> . In <i>Findings of the Association for Compu-</i>	
	<i>tational Linguistics: ACL 2023</i> .	
	Young-Jun Lee, Chae-Gyun Lim, and Ho-Jin Choi.	
	2022. Does gpt-3 generate empathetic dialogues?	
	a novel in-context example selection method and au-	
	tomatic evaluation metric for empathetic dialogue	
	generation. In <i>Proceedings of the 29th International</i>	
	<i>Conference on Computational Linguistics</i> , pages 669–	
	683.	
	Qintong Li, Piji Li, Zhaochun Ren, Pengjie Ren, and	
	Zhumin Chen. 2022. Knowledge bridging for em-	
	pathetic dialogue generation. In <i>Proceedings of</i>	
	<i>the AAAI Conference on Artificial Intelligence</i> , vol-	
	ume 36, pages 10993–11001.	
	Siheng Li, Wangjie Jiang, Pengda Si, Cheng Yang, Qiu	
	Yao, Jinchao Zhang, Jie Zhou, and Yujiu Yang. 2023.	
	<a href="#">Enhancing dialogue generation with conversational</a>	
	<a href="#">concept flows</a> . In <i>Findings of the Association for</i>	
	<i>Computational Linguistics: EACL 2023</i> , pages 1514–	
	1525, Dubrovnik, Croatia. Association for Computa-	
	tional Linguistics.	
	Ye Liu, Wolfgang Maier, Wolfgang Minker, and Ste-	
	fan Ultes. 2022. Conceptnet infused dialogpt for	
	underlying commonsense understanding and reason-	
	ing in dialogue response generation. <i>arXiv preprint</i>	
	<i>arXiv:2209.15109</i> .	
	Yiren Liu and Halil Kilicoglu. 2023. Commonsense-	
	aware prompting for controllable empathetic dia-	
	logue generation. In <i>Proceedings of the Workshop</i>	
	<i>on Knowledge Augmented Methods for Natural Lan-</i>	
	<i>guage Processing</i> .	
	Koh Mitsuda, Ryuichiro Higashinaka, and Yoshihiro	
	Matsuo. 2019. <a href="#">What information should a dialogue</a>	
	<a href="#">system understand?: Collection and analysis of per-</a>	
	<a href="#">ceived information in chat-oriented dialogue</a> . In <i>Ad-</i>	
	<i>vanced Social Interaction with Agents: 8th Interna-</i>	
	<i>tional Workshop on Spoken Dialog Systems</i> , pages	
	27–36. Springer.	
	Nils Reimers and Iryna Gurevych. 2019. Sentence-bert:	
	Sentence embeddings using siamese bert-networks.	
	In <i>Proceedings of the 2019 Conference on Empirical</i>	
	<i>Methods in Natural Language Processing and the 9th</i>	
	<i>International Joint Conference on Natural Language</i>	
	<i>Processing (EMNLP-IJCNLP)</i> , pages 3982–3992.	

- Susan Robinson, David R Traum, Midhun Ittycheriah, and Joe Henderer. 2008. What would you ask a conversational agent? observations of human-agent dialogues in a museum setting. In *LREC*, pages 1–7.
- Sahand Sabour, Chujie Zheng, and Minlie Huang. 2022. Cem: Commonsense-aware empathetic response generation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 11229–11237.
- Siqi Shen, Deepanway Ghosal, Navonil Majumder, Henry Lim, Rada Mihalcea, and Soujanya Poria. 2022. [Multiview Contextual Commonsense Inference: A New Dataset and Task](#). *arXiv preprint*. ArXiv:2210.02890 [cs].
- Robyn Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31.
- Quan Tu, Yanran Li, Jianwei Cui, Bin Wang, Ji-Rong Wen, and Rui Yan. 2022. Misc: A mixed strategy-aware model integrating comet for emotional support conversation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 308–319.
- Deeksha Varshney, Akshara Prabhakar, and Asif Ekbal. 2022. [Commonsense and named entity aware knowledge grounded dialogue generation](#). In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1322–1335, Seattle, United States. Association for Computational Linguistics.
- Ashwin K Vijayakumar, Michael Cogswell, Ramprasath R Selvaraju, Qing Sun, Stefan Lee, David Crandall, and Dhruv Batra. 2016. [Diverse beam search: Decoding diverse solutions from neural sequence models](#). *arXiv preprint arXiv:1610.02424*.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837.
- Sixing Wu, Ying Li, Ping Xue, Dawei Zhang, and Zhonghai Wu. 2022a. [Section-aware commonsense knowledge-grounded dialogue generation with pre-trained language model](#). In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 521–531, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.
- Sixing Wu, Ying Li, Dawei Zhang, and Zhonghai Wu. 2022b. [Generating rational commonsense knowledge-aware dialogue responses with channel-aware knowledge fusing network](#). *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 30:3230–3239.
- Sixing Wu, Ying Li, Dawei Zhang, Yang Zhou, and Zhonghai Wu. 2020. [Diverse and informative dialogue generation with context-specific commonsense knowledge awareness](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5811–5820, Online. Association for Computational Linguistics.
- Houyu Zhang, Zhenghao Liu, Chenyan Xiong, and Zhiyuan Liu. 2020. [Grounded conversation generation as guided traverses in commonsense knowledge graphs](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2031–2043, Online. Association for Computational Linguistics.
- Peixiang Zhong, Di Wang, Pengfei Li, Chen Zhang, Hao Wang, and Chunyan Miao. 2021. Care: commonsense-aware emotional response generation with latent concepts. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 14577–14585.
- Hao Zhou, Tom Young, Minlie Huang, Haizhou Zhao, Jingfang Xu, and Xiaoyan Zhu. 2018. Commonsense knowledge aware conversation generation with graph attention. In *IJCAI*, pages 4623–4629.
- Pei Zhou, Hyundong J. Cho, Pegah Jandaghi, Dong-Ho Lee, Bill Yuchen Lin, Jay Pujara, and Xiang Ren. 2022a. [Reflect not reflex: Inference-based common ground improves dialogue response quality](#). In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*.
- Pei Zhou, Karthik Gopalakrishnan, Behnam Hedayatnia, Seokhwan Kim, Jay Pujara, Xiang Ren, Yang Liu, and Dilek Hakkani-Tur. 2022b. [Think before you speak: Explicitly generating implicit commonsense knowledge for response generation](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1237–1252.

## A Prompts

Tables 5, 6, and 7 show the prompts for ConvoSense-E, ConvoSense-I, and GPT. For all prompts, the dialogue context is provided as a sequence of turns, separated by newlines, where each turn is prefixed by a nominal tag. The terminal turn is prefixed as “Speaker (Other)”, and its preceding utterance is labeled as “Listener (You)”. These nominal tags are then assigned in alternating order to the remainder of the turns and serve to encourage GPT-3.5 to take on the role of the Listener in the conversation when constructing the follow-up response.

## B Output Examples

Examples of the response outputs, commonsense, evaluation explanations, predicted aspects, and mapped categories are shown in Table 8 for the models under study.

## C MTurk Evaluation Interface

Our pilot studies on MTurk reveal that standard worker filtering criteria (Location: USA,CAN; HIT approval  $\geq 98\%$ ; approved HITs:  $\geq 10000$ ) fail to ensure good-faith workers for our evaluation tasks, often yielding invalid or nonsensical explanations. To address this, we introduce a “screening” task identical to the evaluation task, used to identify reliable workers based on their written explanations. This process identifies over thirty MTurkers who provide detailed explanations for their responses. These selected workers then perform the evaluation tasks for our dialogue approaches. The preference evaluation interface used in Section 4.2 is shown in Figure 5.

## D Automated Aspect Identification

Table 9 shows the prompt for automated aspect identification in Section 5.4. The collected human explanations from the evaluation are segmented into batches of 10 and are passed to GPT-3.5 using this prompt.



---

You find yourself in the role of a conversational architect, who is responsible for setting up the next exchange in the ongoing dialogue presented in “Dialogue History.” Specifically, your task is to review the series of talking points provided in “Talking Points” and select the best 1 idea that will craft an engaging and cohesive response for the Listener to say. Write your selected talking point into a list titled “Selection”.

Review the following examples of good selections for different pairs of “Dialogue History” and “Talking Points”.

{examples}

Now, select the best talking point for the following pair:

# Dialogue History  
{context}

# Talking Points  
{inferences}

Selection:

---

You are the Listener in a conversation shown in “Dialogue History”.

Your goal is write a casual yet engaging and appropriate next response for the Listener (You) in the provided dialogue. First, sufficiently answer all questions posed by Speaker (Other) in their preceding turn. Then, continue your response by including the talking points shown in “Talking Points” since you want to cover them in your next response too.

Write the response in the following format:

Listener’s Response:

—

Review the following examples to understand how to write a response given a “Dialogue History” and set of “Talking Points”.

{examples}

Now, complete the tasks for the following situation:

# Dialogue History  
{context}

# Talking Points  
{inferences}

Listener’s Response:

---

Table 5: The Inference Selection (top) and Response Generation (bottom) prompts of ConvoSense-E. {context}, {inferences}, and {examples} are filled by dialogue context, commonsense, and few-shots.

---

You are the Listener in a conversation shown in “Dialogue History”.

Your goal is write a casual yet engaging and appropriate next response for the Listener (You) in the provided dialogue. You will consider a list of possible “Talking Points” to include as you think about the best response to give, being careful to ignore any talking points that are irrelevant or unlikely predictions for the shown conversation.

Based on the talking points, write the best response you can think of in the following format:

Listener’s Response:

—

Review the following examples to understand how to write a response given a “Dialogue History” and set of possible “Talking Points”.

{examples}

Now, construct the best response from the Listener for the following dialogue, based on the possible talking points:

# Dialogue History  
{context}

# Talking Points  
{inferences}

Listener’s Response:

---

Table 6: The prompt used for ConvoSense-I. {context}, {inferences}, and {examples} are filled by dialogue context, commonsense, and few-shots.

---

# Dialogue History  
{context}

You are the Listener in a conversation shown in “Dialogue History”.

Your goal is write a casual yet engaging and appropriate next response for the Listener (You) in the provided dialogue.

Write the response in the following format:

Listener’s Response:

—

Listener’s Response:

---

Table 7: The prompt used for native response generation of GPT. {context} is filled by the dialogue context of a provided example.

DC	<p>Speaker (Other) / B: I had to kick Jan out of my house last night.</p> <p>Listener (You) / A: What got you so mad that you kicked her out of the house?</p> <p>Speaker (Other) / B: She kept bugging the dog and bothering him.</p>			
GPT	That's not cool, dogs need their space too. Did she understand why you were upset with her behavior?			
Doctor	<p>Subquestion 1: What is the reason for Person B's anger towards their neighbor? (xAttr)</p> <p>Subanswer 1: Person B is angry because their neighbor kept bugging the dog and bothering him.</p> <p>Subquestion 2: How does Person A perceive Person B's behavior towards their neighbor? (oReact)</p> <p>Subanswer 2: Person A perceives Person B's behavior as being childish and not helpful towards their neighbor.</p> <p>Subquestion 3: What might Person A want to communicate to Person B, given their perception of Person B's behavior? (oWant)</p> <p>Subanswer 3: Person A might want to express their disapproval of Person B's behavior and suggest that it is not acceptable.</p> <p>That's not a good reason to kick someone out.</p>			
CS-I	<p>* I think the Speaker (Other) feels guilty for having to deal with jan's behavior.</p> <p>* The Listener (You) feels concerned about the well-being of the dog and wonders if there are any underlying issues that could be causing the behavior.</p> <p>* Next, I predict the listener might ask the speaker if they have any other pets in the house.</p> <p>* I think it is possible the previous dialogue turn depends on jan not respecting the boundaries of the house and not being respectful of the speaker's property.</p> <p>* The Listener (You) wants to express sympathy for speaker's situation and offer to help him find a new living situation.</p> <p>* I think it is possible the previous dialogue turn requires jan had access to the dog's living space.</p> <p>* I think it is possible the previous dialogue turn was caused by the dog being a rescue dog and jan being a new owner.</p> <p>* I think the Speaker (Other) wants to find a new place to live that is more peaceful and doesn't have any pets.</p> <p>* I think the Speaker (Other) is someone who takes their pets seriously and doesn't tolerate any behavior that could harm them.</p> <p>* I think the Speaker (Other) is motivated by a need for peace and quiet in their home.</p> <p>That must have been a tough situation. I hope the dog is okay. Do you think it's time for Jan to find a new place to stay?</p>			
CS-E	<p>* I think the Speaker (Other) is motivated by a need for peace and quiet in their home.</p> <p>I can understand why you'd be upset if Jan was bothering your dog. Your home should be a peaceful and safe space for everyone, including your furry friend. How is the dog doing now that Jan's not around?</p>			
EX	vs. GPT	Response A is better overall choice.it shows empathy towards speaker 1's situation,acknowledges the importance of a peaceful environment for both humans and animals ,and expresses concern for the well-being os speaker 1's dog.	<i>empathy</i> <i>acknowledge</i> <i>concern</i>	<b>empathy</b> <b>specific</b> <b>support</b>
	vs. Doctor	Response B is better as it shows more concern, expresses understanding and empathy for their situation.	<i>concern</i> <i>understanding</i> <i>empathy</i>	<b>support</b> <b>support</b> <b>empathy</b>
	vs. ConvoSense-I	The given response is more relevance to the conversation and make more comprehensive	<i>relevance</i> <i>comprehensive</i>	<b>relevant</b> <b>detailed</b>

Table 8: Example response outputs for a dialogue context (DC) from each model, including commonsense where applicable. CS-E/I denote ConvoSense-E/I. Example explanations provided by human evaluators for the preference for ConvoSense-E against all other models are also shown (EX), along with the *predicted aspects* from the automatic identification procedure and their **corresponding mapped categories**.

We are studying different methods for communicating in dialogues.

You will be shown a dialogue and two options for the next response.

Your tasks are: (1) **comparing which response is better** in terms of various aspects and (2) **explaining in freeform text** your selection of the best overall response.

**Guidelines:**

(1) [Q1-4] **First, choose which response is better for each given aspect.** There are four choices: **Definitely A/B** and **Slightly A/B**.

- Please trust your instincts and choose **Definitely** if you feel more confident choosing one response over the other one.
- Try to focus on content over length. Responses do not need to be lengthy to be a good fit to the aspects.

(2) [Q5] **After, please explain your selection of which response had the best overall quality.**

- It is most useful for us if you could describe what characteristics made one response better than the other.
- Please be specific in your explanation. You must enter a minimum of 15 characters and no copy-paste is allowed.

**Dialogue Context**

`\${dialogue\_context}`

**Response A**

`\${response\_a}`

**Response B**

`\${response\_b}`

[Q1] Which response is more **natural** (human-like) as the next response in the dialogue?

- ☒ Definitely A ☐ Slightly A ☐ Slightly B ☐ Definitely B

[Q2] Which response is more **engaging and interesting** as the next response in the dialogue?

- ☒ Definitely A ☐ Slightly A ☐ Slightly B ☐ Definitely B

[Q3] Which response contains content that is **more specific and unique** to the shown dialogue?

- ☒ Definitely A ☐ Slightly A ☐ Slightly B ☐ Definitely B

[Q4] Which response demonstrates better **overall quality** as the next response in the dialogue?

- ☒ Definitely A ☐ Slightly A ☐ Slightly B ☐ Definitely B

[Q5] Explain your reasoning behind which response had best overall quality:

Figure 5: Evaluation interface.



---

I have received feedback from human judges explaining their preference for a certain dialogue response from the options displayed to them. For each of the following explanations, please list the positive aspects identified. Aspects should be one word only, so please summarize the positive traits identified into one word if needed. Examples of aspects that could be mentioned are empathy, engagement, curiosity, acknowledgement, support, naturalness, and more.

Output a list of aspects for each explanation below.

{explanations}

---

Table 9: The prompt used for automated aspect identification of human preference explanations. {explanations} is filled with human explanations as a numbered list.