

# PCQPR: Proactive Conversational Question Planning with Reflection

Shasha Guo<sup>1, 2\*</sup>, Lizi Liao<sup>3</sup>, Jing Zhang<sup>1, 2</sup>, Cuiping Li<sup>1, 2</sup>, Hong Chen<sup>1, 2</sup>

<sup>1</sup>School of Information, Renmin University of China, Beijing, China

<sup>2</sup>Key Laboratory of Data Engineering and Knowledge Engineering of Ministry of Education

<sup>3</sup>Singapore Management University

{guoshashaxing, zhang-jing, licuiping, chong}@ruc.edu.cn, lzliao@smu.edu.sg

## Abstract

Conversational Question Generation (CQG) enhances the interactivity of conversational question-answering systems in fields such as education, customer service, and entertainment. However, traditional CQG, focusing primarily on the immediate context, lacks the conversational foresight necessary to guide conversations toward specified conclusions. This limitation significantly restricts their ability to achieve conclusion-oriented conversational outcomes. In this work, we redefine the CQG task as Conclusion-driven Conversational Question Generation (CCQG) by focusing on proactivity, not merely reacting to the unfolding conversation but actively steering it towards a conclusion-oriented question-answer pair. To address this, we propose a novel approach, called **Proactive Conversational Question Planning with self-Refining (PCQPR)**. Concretely, by integrating a planning algorithm inspired by Monte Carlo Tree Search (MCTS) with the analytical capabilities of large language models (LLMs), PCQPR predicts future conversation turns and continuously refines its questioning strategies. This iterative self-refining mechanism ensures the generation of contextually relevant questions strategically devised to reach a specified outcome. Our extensive evaluations demonstrate that PCQPR significantly surpasses existing CQG methods, marking a paradigm shift towards conclusion-oriented conversational question-answering systems.

## 1 Introduction

Conversational Question Generation (CQG) has significantly enhanced the capabilities of conversational question-answering (QA) systems, bringing a level of dynamism and intelligence that was previously unattainable. In various fields such as educational technology, customer service, and interactive

\*This work was done during an internship at SMU.

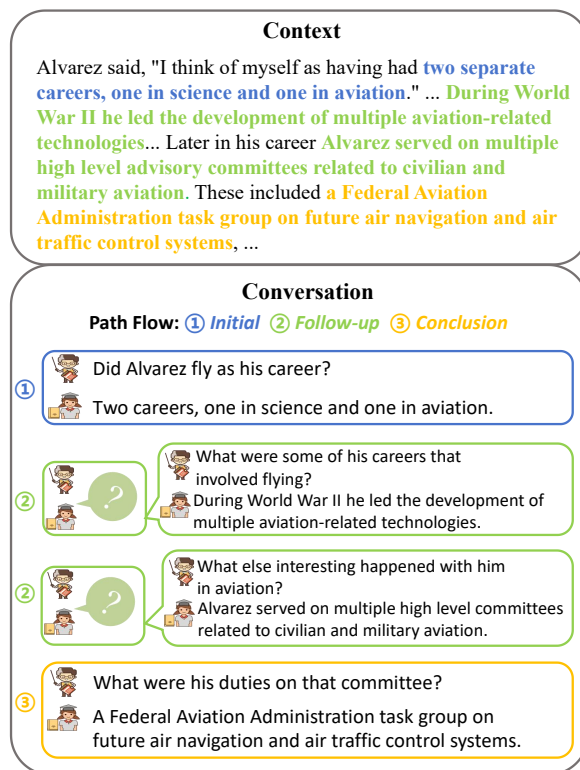


Figure 1: An example of CCQG. Given the specific context, the initial conversation (blue), and the concluding question-answer pair (orange), CCQG proactively generates subsequent questions (green), aiming to advance toward the predefined question-answer pair.

entertainment, CQG has become a crucial component for enhancing user interactions, enabling more natural and responsive conversations between humans and machines. By generating contextually appropriate questions, CQG systems have improved the interactive experience, making conversations with AI more engaging and informative.

Despite these advancements, current CQG methods are predominantly reactive, generating questions based solely on the immediate context without strategically considering the specified conversational outcome. This reactivity is evident in various existing approaches: from choosing the most rel-

evant conversational history to enhance question relevance (Do et al., 2022), to utilizing a context-enhanced neural model for identifying key contexts (Ling et al., 2023), and designing a two-stage framework for generating more natural conversations (Do et al., 2023). While these methods contribute significantly to the field, their inherent reactivity limits their potential to direct conversations toward specific, predetermined conclusions.

These identified limitations underscore the necessity for a paradigm shift towards proactiveness in CQG, leading us to propose the novel task of Conclusion-driven Conversational Question Generation (CCQG), as illustrated in Figure 1. CCQG emphasizes the strategic generation of questions to guide conversations toward specific outcomes, a critical capability that reactive models fail to support adequately. By focusing on proactive question generation, we aim to overcome the limitations of reactivity and enable more purposeful and outcome-oriented question-answering conversations.

In contrast to conversational QA systems, the field of proactive dialogue systems has recently seen the emergence of several frameworks designed to accurately predict user needs and steer conversations accordingly. Methods such as the application of MCTS for dialogue planning (Yu et al., 2023; Zhang et al., 2023; Zhao et al., 2023), and the use of large language models (LLMs) for predicting conversation trajectories (Deng et al., 2022; Dao et al., 2023; Liao et al., 2023), represent significant strides towards proactive dialogue management. However, these approaches do not directly address the nuanced requirements of CCQG, which relies on strategically generating questions to guide conversations toward specified outcomes.

To bridge this gap, we propose the **Proactive Conversational Question Planning with self-Refining (PCQPR)** framework, which innovatively integrates strategic planning and reflective refinement. By incorporating an MCTS-like planning algorithm with the analytical capabilities of LLMs, our approach utilizes LLMs to predict and simulate future conversation paths, thus guiding the question generation toward the specified, desired outcome. Concurrently, LLMs engage in reflective analysis of these simulations, providing critical feedback for each action within the simulation paths to inform and enhance conversational strategies. This reflective analysis identifies failures and showcases successful experiences, providing a balanced and thorough evaluation of each planning path. By adopting

the comparable reflection mechanism that captures errors and successes, the framework guarantees the systematic incorporation of insights, leading to progressively enhanced question generation. The PCQPR framework’s innovative use of LLMs for both forward-looking simulation and reflective feedback marks a strategic shift from reactive to proactive CQG, aligning conversations more effectively with specified outcomes.

**Main Contributions.** (1) We propose a novel CCQG task that emphasizes proactive conversation steering in conversational question-answering systems. (2) We introduce an advanced PCQPR framework that uniquely integrates strategic planning with reflective refinement. Using MCTS-like algorithms and a reflection strategy, it predicts future conversation paths and provides critical feedback, continuously improving question generation. (3) Extensive experiments validate the effectiveness of PCQPR, demonstrating its superior performance and marking a notable advancement in proactive conversational question-answering systems.

## 2 Related Work

**Question Generation.** Question Generation (QG) aims to generate questions from diverse inputs, including text (Fei et al., 2022; Gou et al., 2023), knowledge base (Chen et al., 2023; Liang et al., 2023; Guo et al., 2022, 2024b,c), and so on. Traditionally, QG has played a pivotal role in numerous practical applications, focused on producing contextually appropriate and meaningful questions (Guo et al., 2024a).

Recently, research has increasingly focused on Conversational Question Generation (CQG), which emphasizes multi-turn interactions to better simulate dynamic and natural conversational scenarios. In this domain, frameworks such as that proposed by Gu et al. (2021) incorporate answer encoders and QG modules to learn from each conversational turn and generate subsequent questions. Similarly, Do et al. (2022) apply top- $p$  strategies to select pertinent conversation history, thereby enhancing question relevance. Other notable approaches include Ling et al. (2023)’s context-enhanced neural model for identifying key contexts in question generation, and Zeng et al. (2023)’s Zero-shot CQG, which utilizes transfer learning for multi-turn scenarios from single-turn QG instances. Furthermore, the ‘what to ask’ and ‘how to ask’ modules of Do et al. (2023)’s two-stage framework further high-

light the evolving complexity in CQG.

Despite these developments, most CQG approaches remain reactive, focusing on generating questions from existing conversational content. To bridge this gap, we propose Conclusion-driven Conversational Question Generation (CCQG). CCQG departs from the reactive nature of traditional CQG, aiming to proactively generate a series of questions that guide the conversation toward a specified outcome. This novel task represents a strategic shift towards outcome-oriented conversation management in conversational QA systems.

The CCQG task holds significant practical value across various domains. For example, in intelligent tutoring systems, CCQG can guide students through structured sequences of questions, tailored to their current understanding, thereby personalizing and enhancing the educational experience. In Customer Service, particularly in troubleshooting scenarios, guiding a conversation toward a specific resolution is critical. Often, customers may not know the exact problem they face. A CCQG system can lead the customer through diagnostic questions, efficiently identifying the issue and guiding them to the appropriate solution. In interactive storytelling or role-playing games, the narrative’s richness depends on how well the system can guide the user through the story. CCQG enhances user experience by maintaining narrative coherence and leading them to key plot points. By integrating CCQG into these systems, we aim to shift conversational interactions from passive question generation to an active, outcome-driven process.

**Planning and Reflection.** In the field of Natural Language Processing (NLP), planning has emerged as a crucial strategy, particularly for achieving specific targets through a series of intermediate actions. Recent advancements have seen the utilization of LLMs in various planning-based NLP tasks, evidenced by approaches such as Chain-of-Thought (CoT) reasoning (Wei et al., 2022), CoT with self-consistency (Wang et al., 2023), Reasoning via Planning (RAP) (Hao et al., 2023), and Tree of Thoughts (TOT) (Yao et al., 2023). These methods illustrate the capability of LLMs to generate structured, step-by-step solutions. However, they often employ a linear, simplistic planning model that lacks iterative feedback, which can constrain their adaptability in dynamic NLP tasks.

To address the above challenges, recent approaches have incorporated reflection from LLMs

as feedback (Madaan et al., 2023; Shinn et al., 2023; He et al., 2024) to refine planning processes. This shift represents a movement towards more dynamic planning, emphasizing the iterative improvement of individual plans. However, these methods primarily enhance single action sequences and do not fully explore multiple concurrent paths. In our work, PCQPR introduces a novel combination of a tree search algorithm with reflective refinement, facilitating complex, multi-path planning. This approach differs from traditional methods by evaluating various potential actions at each planning step, ensuring that the generated questions are precisely aligned with the desired outcome.

### 3 Problem Formulation

A conversational question generation dataset<sup>1</sup> is denoted as  $\mathcal{D} = \{C_i, H_i, T_i, \mathcal{G}_i\}_{i=1}^N$  with  $N$  as the total number of conversations.  $C_i = \{s_1, s_2, \dots, s_m\}$  with  $m$  sentences represents the context related to the  $i$ -th conversation.  $H_i = \{(q_1, an_1), (q_2, an_2), \dots, (q_t, an_t)\}$  with  $t$  question-answer pairs represents the conversational history in the  $i$ -th conversation.  $T_i$  denotes the predefined conclusion consisting of a question-answer pair  $(q_n, an_n)$ .  $\mathcal{G}_i = \{(q_{t+1}, an_{t+1}), (q_{t+2}, an_{t+2}), \dots, (q_{n-1}, an_{n-1})\}$  represents the ground-truth responses to achieve the specified outcome  $T_i$ . The task of CCQG is formalized as follows: given a predefined outcome  $T_i$ , a context  $C_i$ , and a conversation history  $H_i$ , the objective of CCQG is to proactively guide the conversation to generate desired responses<sup>2</sup>  $\hat{\mathcal{G}}_i$ , thereby reaching the predefined outcome  $T_i$ .

## 4 Methodology

### 4.1 Overview

To address the CCQG task, we propose a novel framework called PCQPR, designed to proactively steer the conversation towards achieving the specified outcome. The framework initially employs the Monte Carlo Tree Search-like (MCTS-like) algorithm for planning, performing a lookahead search to generate the desired response. Subsequently, it

<sup>1</sup>Since CCQG is a novel task, there is no directly available dataset. The original datasets do not explicitly state the pre-determined conclusions, so we have restructured the data into the format we are currently using.

<sup>2</sup>In our paper, “response” refers to a question-answer pair. However, we sometimes use “question” interchangeably with “response” since the context frequently makes the answer evident once the question is posed.

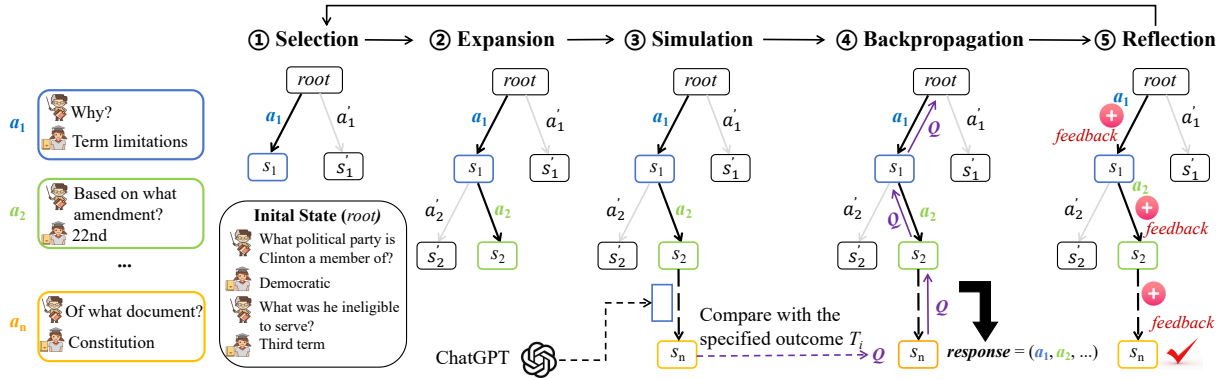


Figure 2: An overview of our PCQPR framework. Specifically, the framework employs MCTS-like for planning, performing a lookahead search to generate the desired response (marked in **black**). Subsequently, it leverages a comparable reflection strategy to elevate the quality of this response (marked in **red**).

leverages the comparable reflection strategy to elevate the quality of this response. The framework details are illustrated in Figure 2. In planning, we innovatively integrate MCTS-like algorithms with LLMs, significantly narrowing the search space through efficient exploration. Concurrently, we prioritize achieving the specified outcome as the primary objective, thereby enhancing the overall effectiveness of our planning methodology (see Section 4.2). In the comparable reflection strategy, we utilize LLMs to iteratively generate verbal feedback for each action along the planning path, facilitating learning from past failures and successful experiences. This continuous refinement enhances response quality, ensuring the achievement of the specified outcome (see Section 4.3).

## 4.2 Planning with Monte Carlo Tree Search

We explain how to (1) formulate the CCQG task as a Markov decision process (MDP) and (2) solve it by MCTS-like planning algorithm.

### 4.2.1 MDP

For the CCQG task, we utilize the LLM (e.g., ChatGPT) to generate an action for the current state, thereby obtaining the next state. Specifically, a state  $s$  is the concatenation of the context  $C_i$ , the conversation history  $H_i$ , and the partially or completely generated response  $\hat{G}_i$ , where the complete response signifies the attainment of the designated outcome  $T_i$ . An action  $a$  comprises a question-answer pair that forms the basis of the complete response. The terminal action matches or closely mirrors the predefined outcome, indicating the achievement of the desired goal. The transition function systematically combines a state  $s$  with an action  $a$ . An episode concludes once the LLM executes the

terminal action. To accurately evaluate the state  $s$ , the reward for  $s$  is determined by how closely the responses reach a specified outcome, given that  $s$  matches or closely resembles the predefined outcome<sup>3</sup>, i.e.,  $\text{REWARD}(\text{response})$  (line 17 in Algorithm 1). If the response fails to meet the specified outcome, the reward is set to 0.

To determine the optimal policy in an MDP, we explore a tree search-based planning algorithm, drawing inspiration from MCTS (Yu et al., 2023; Zhang et al., 2023; Zhao et al., 2023). More concretely, the tree search algorithm, inherently structured like a tree, assigns nodes to represent various states and uses edges to indicate actions. This algorithm begins at the root node, which is the initial state, and it explores the state space to identify terminal states with high rewards. Each node in the tree search algorithm encompasses two essential elements: *the visited number* and *a value function*. The visited number indicates how many times each node has been visited, while the value function represents the maximum reward obtained by starting from the node (or state)<sup>4</sup>  $s$  and executing action  $a$ . The algorithm effectively maintains a proper balance between exploration and exploitation. In the subsequent portion of this section, we detail the method of incorporating the tree search algorithm into the planning procedure.

### 4.2.2 MCTS-like Planning

To effectively guide the conversation toward a specified outcome, we develop an LLMs-based plan-

<sup>3</sup>We calculate the reward by measuring the semantic similarity between the predefined outcome and the terminal action using embeddings from SimCSE (Gao et al., 2021). In this paper, we set the semantic similarity threshold at 0.6.

<sup>4</sup>A node is defined to represent the state it embodies.

ning algorithm, which utilizes an MCTS-like tree search performing lookahead planning. We summarize the entire procedure in Algorithm 1 and illustrate the process in Figure 2. More specifically, the planning process encompasses five critical operations: *selection*, *expansion*, *simulation*, *backpropagation*, and *comparable reflection*.

**Selection.** This phase selects a branch of the tree for further exploration. Starting from the root node, representing the initial state  $s$ , the algorithm sequentially selects a child node until it reaches a leaf node. To balance between exploration (*focusing on less-visited nodes*) and exploitation (*targeting high-value nodes*), we employ a function similar to the widely recognized Upper Confidence Bounds (UCB) (Kocsis and Szepesvári, 2006) function to select each child node, which we refer to as UCB-like. Unlike the UCB function, we use the probability of reaching the designated outcome for the exploitation term. Formally, UCB-like function is defined as :

$$\text{UCB-like}(s) = Q(s, a) + w \sqrt{\frac{\log N(p)}{N(s)}}, \quad (1)$$

where  $Q(s, a)$  is the maximum reward obtained by starting in  $s$  and taking action  $a$ ,  $N(p)$  is the number of visits for parent node  $p$  of  $s$ ,  $N(s)$  is the number of visits to a node  $s$ , and  $w$  is the exploration weight. At each level, the child node with the highest UCB-like value is selected.

**Expansion.** From the node selected in the selection step, we derive  $k$  possible actions and generate  $k$  new states. These states form new nodes added to the list of children. More specifically, we use powerful LLMs (*e.g.*, ChatGPT) to identify the most probable next actions, formalized as the function  $\text{TOP\_K}(s, k)$ , which returns the  $k$  likeliest actions from state  $s$ . The corresponding  $k$  new states are created by combining the current state with each action, and these new states are added to the list of children of the current node.

**Simulation.** We calculate the expected reward (*i.e.*,  $Q$  value) by leveraging LLMs (*e.g.*, ChatGPT) to simulate potential scenarios from the current node. Starting at the current node, LLMs generate actions sequentially until a terminal action is reached or a maximum number of steps is completed. We then assess the semantic similarity between the final action and the specified outcome  $T_i$ . This similarity serves as the reward for the current node, measuring its relevance to the outcome.

---

### Algorithm 1: The PCQR algorithm

---

**Input:** The initial state  $s$  (or *root*), the number of children for each node  $k$ , UCB-like exploration parameter  $w$ .  
**Output:** Response with the highest reward.  
1: Initialize the  $\text{response\_dict} = \text{OrderedDict}()$   
2: **for**  $i \leftarrow 1, 2, \dots, \text{max\_iterations}$  **do**  
3:    $\text{node} \leftarrow \text{root}$   
4:   # Selection  
5:   **while**  $|\text{node.children}| > 0$  **do**  
6:      $\text{node} \leftarrow \text{UCB-like}(\text{node.children})$   
7:   **end while**  
8:   # Expansion  
9:    $\text{next\_actions} \leftarrow \text{TOP\_K}(\text{node}, k)$   
10:   **for**  $\text{next\_action} \in \text{next\_actions}$  **do**  
11:      $\text{next\_state} \leftarrow \text{COMBINE}(\text{node}, \text{next\_action})$   
12:      $\text{new\_node} \leftarrow \text{new\_state}$   
13:     Append  $\text{new\_node}$  to children of  $\text{node}$   
14:   **end for**  
15:   # Simulation  
16:    $\text{response} \leftarrow \text{LLM}(\text{node})$   
17:    $\text{reward} \leftarrow \text{REWARD}(\text{response})$   
18:    $\text{response\_dict}[\text{response}] = \text{reward}$   
19:   # Backpropagation  
20:   Update the values of  $\text{node}$  and its ancestors with  $\text{reward}$   
21:   # Reflection  
22:    $\text{feedback} \leftarrow \text{COMP\_REFINE}(\text{response})$   
23:   Add the  $\text{feedback}$  into  $\text{node}$  and its ancestors  
24: **end for**  
25: **Return**  $\text{response}$  with the highest reward in  $\text{response\_dict}$ .

---

**Backpropagation.** Following the simulation phase, we can obtain a path sequence of actions from the root node to the terminal node, denoted as  $\text{response}$ , and acquire the corresponding reward value associated with this path. Subsequently, this reward is backpropagated to revise the  $Q$  value of each state-action pair encountered along the path. Ultimately, the  $Q$  value of every node in this path is updated to reflect the simulation results accurately.

### 4.3 Comparable Reflection

Although the MCTS-like planning algorithm demonstrates commendable performance in the CCQG task, there is significant potential for further improvement. Notably, some initial planning paths fail to achieve the desired outcomes, underscoring the need for a more refined approach to enhance the algorithm’s effectiveness. Inspired by human cognitive strategies, which learn from past *successes* and *failures* to improve future performance, we propose an enhancement for the MCTS-like planning algorithm through a comparable reflection mechanism that summarizes both errors and successful experiences. This mechanism provides the algorithm with detailed verbal feedback on previous planning paths, enabling it to optimize future

decision-making processes.

To implement this enhancement, we integrate a self-reflection mechanism powered by advanced LLMs (e.g., ChatGPT). This marks a significant advancement in the MCTS-like planning algorithm’s effectiveness for the CCQG task. The sophisticated analytical capabilities of LLMs (Liang et al., 2024) enable comprehensive evaluations of planning paths, generating detailed verbal reflections for each sequence of actions (i.e., COMP\_REFINE(response), see line 22 in Algorithm 1). These reflections serve as a semantic guidance signal, providing the algorithm with concrete directions for improvement by pinpointing failure points and highlighting successful strategies. This balanced view of what works and what doesn’t fosters a deeper comprehension of the decision-making dynamics, enabling the detection of patterns that lead to both suboptimal results and successful outcomes. The algorithm can be finely tuned by systematically analyzing these patterns to anticipate and circumvent similar pitfalls while replicating successful strategies in future iterations. This reflective process provides valuable insights that optimize the algorithm’s behavior, enhancing its ability to solve complex scenarios through iterative trials and self-reflection.

For example, in planning, there are two initial planning paths: a failed path  $p_1 = (a_1, \dots, a_n)$  where the terminal action  $a_n$  diverges from the outcome  $T_i$ , and a successful path  $p_2 = (a'_1, \dots, a'_n)$  where the terminal action  $a'_n$  matches the outcome  $T_i$ . The comparable reflection mechanism provides fine-grained feedback for two planning paths. For the failed path  $p_1$ , it identifies the points of divergence and reasons for failure, providing critical feedback on what went wrong. Conversely, for the successful path  $p_2$ , it recognizes the key decisions that led to a positive outcome, reinforcing effective strategies. This dual analysis ensures that the algorithm not only learns from its mistakes but also builds on its successes, leading to continuous improvement and more reliable planning outcomes. This comparable reflection mechanism ensures that future iterations of the planning algorithm are better equipped to handle similar situations, ultimately enhancing performance and decision-making capabilities in complex scenarios. To the best of our knowledge, we are the first to combine a tree search algorithm with a comparable reflection strategy to enhance the performance of the novel CCQG task.

## 5 Experiments

### 5.1 Experimental Settings

**Datasets.** As the novel task setting of CCQG has not been investigated in prior research, no direct dataset is available. Hence, we modify two popular conversational datasets (i.e., CoQA (Reddy et al., 2019) and QuAC (Choi et al., 2018)) to meet the requirements of the CCQG task. For the CoQA dataset, we standardize the number of turns in all conversations to 10 because some have too many turns. For the QuAC dataset, we include only conversations where the turn is labeled with ‘followup: y’ or ‘followup: m’, resulting in a training set of 2,749 conversations and a validation set of 221 conversations. We use the last three question-answer pairs as the target pairs. The two datasets comprise conversations across a wide range of domains, where each conversation consists of a relevant context and several question-answer pairs. Following prior studies (Do et al., 2023), we use the validation sets from two datasets as our test sets since the original test sets are unavailable.

**Automatic Evaluation Metrics.** We employ widely used evaluation metrics for text generation, including BLEU (Papineni et al., 2002) and METEOR (Banerjee and Lavie, 2005), to evaluate the generated response. Concretely, BLEU evaluates the precision of the generated text compared to the reference text. METEOR is a detailed evaluation considering exact words, synonyms, and similar phrases. Additionally, we employ SimCSE (Gao et al., 2021) to measure conversational coherence. This method regards the generated response as the premise, while the previous conversational history serves as the hypothesis. It then calculates a similarity score between them to assess topic coherence. In our experiments, we assess the conversation coherence score by focusing on the last one and last two prior turns, referred to as Conv-last1 and Conv-last2, respectively. Furthermore, the most pivotal metric is the Success Rate, i.e.,  $\text{Success Rate} = \frac{\text{Number of Successful Outcomes}}{\text{Total Number of Instances}}$ , which is employed to measure the capacity to achieve the intended conversational outcome.

**Human Evaluation Metrics.** Due to the extensive critique of automatic metrics for their poor alignment with human assessments (Novikova et al., 2017), we incorporate two human evaluation metrics: Coherence and Effectiveness. The former metric evaluates whether the entire conversation main-

Model	BLEU	METEOR	Conv-last1	Conv-last2	Success Rate
SG-CQG	3.62	46.35	32.77	40.04	15.40
COT	3.86	46.62	31.39	39.48	19.20
COT-SC	6.85	53.45	30.84	38.86	10.40
TOT	<b>7.05</b>	<b>54.81</b>	29.85	37.96	23.20
Mixtral-8x7B	1.96	46.93	29.26	36.65	6.20
ChatGPT	3.31	45.57	31.09	39.19	19.80
GPT-4-Turbo	5.28	52.48	30.29	37.53	12.80
PCQPR(Mixtral-8x7B)	1.54	44.87	34.78	40.62	25.80
PCQPR(ChatGPT)	3.56	50.07	36.13	42.31	28.00
PCQPR(GPT-4-Turbo)	6.47	54.04	<b>37.39</b>	<b>43.06</b>	<b>35.00</b>

Table 1: Overall evaluation on CoQA (%).

Model	BLEU	METEOR	Conv-last1	Conv-last2	Success Rate
COT	11.17	41.87	46.13	50.86	30.32
COT-SC	<b>23.38</b>	<b>51.82</b>	46.79	51.09	22.62
TOT	13.74	46.09	48.19	52.48	40.27
Mixtral-8x7B	7.45	39.77	44.75	49.68	23.98
ChatGPT	11.02	41.29	46.04	50.33	27.60
GPT-4-Turbo	7.85	40.46	44.55	49.42	26.24
PCQPR(Mixtral-8x7B)	5.64	38.84	51.85	56.11	63.35
PCQPR(ChatGPT)	9.38	41.41	52.87	56.06	67.42
PCQPR(GPT-4-Turbo)	7.59	42.47	<b>54.54</b>	<b>57.49</b>	<b>70.59</b>

Table 2: Overall evaluation on QuAC (%).

tains logical and topic coherence, while the latter assesses the efficiency with which the intended conversational outcome is achieved. We randomly select 50 conversations from the validation set of the CoQA dataset and invite three individuals to score the generated responses, with a scoring range of  $\{0, 1, 2\}$ , where a higher score indicates better quality in terms of Coherence and Effectiveness. Detailed scoring criteria are provided in Appendix A.2. We use Fleiss’s kappa (Fleiss, 1971) to measure the consistency among the three persons.

**Baselines.** Since this novel task setting has not been fully explored in previous work, there are no readily available baselines for comparison. Therefore, we have modified the seven most relevant baselines for comparison. Among them, SG-CQG (Do et al., 2023), an advanced CQG model assessed on the CoQA dataset, proposes a two-stage method including a ‘what-to-ask’ module and a ‘how-to-ask’ module. The most popular open-source model, Mixtral-8x7B (Jiang et al., 2024), along with two closed-source models, ChatGPT<sup>5</sup> and GPT-4-Turbo (Achiam et al., 2023), are employed in a zero-shot setting to address this task. COT (Wei et al., 2022) and its variants, COT-SC (Wang et al., 2023) and TOT (Yao et al., 2023)

utilize ChatGPT as the backbone to solve this task.

## 5.2 Overall Evaluation

Table 1 and Table 2 show the overall evaluation results for the CoQA and QuAC datasets, we can conclude that: **(1) Our proposed framework, PCQPR, can produce more logically coherent responses.** Compared with baselines, our approaches (*e.g.*, PCQPR(ChatGPT) and PCQPR(GPT-4-Turbo)) excel in generating more coherent responses that align with the conversational history (Conv-last1 and Conv-last2), indicating their impressive abilities in conversational understanding and response generation. For instance, on the CoQA dataset, PCQPR(GPT-4-Turbo) achieves absolute improvements of 4.62% in Conv-last1 and 3.02% in Conv-last2 over the best baseline (*i.e.*, SG-CQG). **(2) Our approach naturally transitions into the specified outcome with the highest success rate, demonstrating its effectiveness.** We observe that our best method (*i.e.*, PCQPR(GPT-4-Turbo)) achieves an 11.8% improvement in Success Rate over the best baseline (*i.e.*, TOT) on CoQA. Additionally, on the CoQA dataset, PCQPR(GPT-4-Turbo) derives a 22.2% Success Rate gain over its corresponding vanilla model GPT-4-Turbo. PCQPR(ChatGPT) obtains an 8.2% Success Rate gain over its correspond-

<sup>5</sup><https://openai.com/blog/chatgpt>

ing vanilla model ChatGPT. **(3) Our approach not only produces logically coherent responses but also effectively steers the conversation toward the predetermined outcome.** PCQPR(GPT-4-Turbo) derives 37.39% Conv-last1, 43.06% Conv-last2, and 35.00% Success Rate on CoQA. Compared to the best baseline results, SG-CQG exhibits the highest coherence, achieving 32.77% Conv-last1 and 40.04% Conv-last2, while TOT shows the highest Success Rate at 23.20%. Our proposed framework demonstrates superiority in both aspects. **(4) Our method has comparable performance in BLEU and METEOR with the best baseline.** We observe that the best baseline TOT derives 7.05% BLEU and 54.81%, while our method PCQPR(GPT-4-Turbo) achieves 6.47% BLEU and 54.04% on CoQA. Although there are gaps, this does not mean that our approach is inferior to the baseline. Because BLEU and METEOR metrics are less reliable, they measure the lexical surface similarity between the produced response and the ground-truth response. But conversations on the same topic can be described in different ways, rather than just ground-truth responses. Therefore, we focus primarily on reliable metrics of conversational coherence (*i.e.*, Conv-last1 and Conv-last2) and effectiveness (*i.e.*, Success Rate).

### 5.3 Human Evaluation

To comprehensively validate the effectiveness of our approach, we conduct a rigorous human evaluation. This involves providing scorers with detailed examples, designed to guide them towards objective and fair assessments of generated responses. The results presented in Table 3 demonstrate the superiority of our method compared to traditional baselines. Notably, our approach shows superiority in terms of conversational coherence (*i.e.*, “Coherence”) and in successfully reaching the designated conversational outcome (*i.e.*, “Effectiveness”). These two aspects are crucial in assessing the quality of conversational question-answering systems, as they directly reflect the system’s ability to maintain a natural and purposeful conversation flow. To ensure the reliability of these evaluation results, we further employ Fleiss’s kappa, a statistical measure designed to assess the consistency of agreement among multiple scorers. The kappa values range between 0.41 and 0.60, indicating moderate agreement among the three scorers. This range suggests a reasonable consensus, lending further credibility to our results.

Model	Coherence	Effectiveness
SG-CQG	1.28	1.14
TOT	1.16	1.25
Mixtral-8x7B	1.12	0.91
ChatGPT	1.23	1.20
GPT-4-Turbo	1.18	1.06
PCQPR(Mixtral-8x7B)	1.33	1.29
PCQPR(ChatGPT)	1.65	1.34
PCQPR(GPT-4-Turbo)	1.68	1.62
kappa	0.46	0.53

Table 3: Human evaluation results on CoQA.

Model	Conv-last1	Success Rate
PCQPR(Mixtral-8x7B)	34.78	25.80
- w/o MCTS	28.69	14.60
- w/o Reflection	34.80	15.40
PCQPR(ChatGPT)	36.13	28.00
- w/o MCTS	30.16	26.80
- w/o Reflection	36.18	22.00
PCQPR(GPT-4-Turbo)	37.39	35.00
- w/o MCTS	29.03	14.60
- w/o Reflection	36.85	30.60

Table 4: Ablation studies for PCQPR on CoQA (%).

## 5.4 Ablation Studies

To verify the effectiveness of PCQPR, we conduct extensive ablation experiments.

### 5.4.1 Effect of MCTS-based Planner

To investigate the effectiveness of our proposed MCTS-based planner, we conduct an experiment where the MCTS-based planner is removed, denoted as “w/o MCTS”. Table 4 reports the results on Conv-last1 and Success Rate. We observe that removing the MCTS-based planner results in a reduction of 8.36% in Conv-last1 score and 20.4% in Success Rate for our method, PCQPR(GPT-4-Turbo). A reasonable explanation is that the MCTS-based planner performs a lookahead search and finds high-quality responses toward the predefined outcome. Consequently, the MCTS-based planner we designed plays a crucial role in our framework.

### 5.4.2 Effect of Reflection Strategy

We evaluate the impact of the reflection strategy on our proposed approach. This involves a contrastive analysis, termed “w/o Reflection”, specifically designed to measure the contribution of this strategy. As shown in Table 4, the results indicate a significant performance decrease in the absence of reflection: a 10.4% drop in Success Rate for PCQPR(Mixtral-8x7B). This decline underscores



the reflection strategy’s vital role, in which verbal feedback integration facilitates an iterative learning process. This process enables the model to refine its response generation based on previous outcomes, improving relevance and accuracy. Therefore, the reflection strategy elevates performance and marks a significant advancement in conversational question-answering systems. It enhances the model’s adaptability and effectiveness, particularly in dynamic and evolving conversational contexts, thereby underscoring its importance in developing more sophisticated, responsive systems.

## 6 Conclusion

We present a novel task setting, CCQG, designed to generate subsequent questions that proactively guide conversations toward the specified outcome. To address this task, we propose an innovative framework, PCQPR, which uniquely combines the MCTS-like planning algorithm with LLMs to enhance planning capabilities. This approach conducts a lookahead search to explore multiple potential paths. Furthermore, we introduce a novel reflection mechanism that provides insightful verbal feedback for each action along the entire planning path. Extensive experiments demonstrate the superior performance of PCQPR over closed-source and open-source LLMs. We believe this effort could be inspiring for future research in AI-driven conversational question-answering systems.

## Acknowledgments

This work is supported by the National Key Research & Develop Plan (2023YFF0725100) and the National Natural Science Foundation of China (62322214, U23A20299, 62076245, 62072460, 62172424, 62276270). This work is supported by Public Computing Cloud, Renmin University of China. We also acknowledge the support from the China Scholarship Council Scholarship Fund. We sincerely appreciate the valuable and insightful feedback provided by all reviewers.

## Limitations

Despite the effectiveness of the comparable self-reflection strategy, it still exhibits certain limitations. This paper primarily focuses on leveraging large language models (LLMs) to provide valuable verbal feedback and refine each action within the entire planning path. However, we recognize that the inherent capabilities of LLMs may constrain

their effectiveness. In particular, for some paths that initially succeed in reaching the specific outcome, the reflection strategy may not yield further improvements. In future work, we will explore optimal methods for integrating human feedback with verbal reflection generated by LLMs to address this challenge above effectively.

## References

- Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, pages 1–100.
- Satanjeev Banerjee and Alon Lavie. 2005. METEOR: an automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization@ACL 2005*, pages 65–72.
- Yu Chen, Lingfei Wu, and Mohammed J. Zaki. 2023. Toward subgraph-guided knowledge graph question generation with graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, pages 1–12.
- Eunsol Choi, He He, Mohit Iyyer, Mark Yatskar, Wentau Yih, Yejin Choi, Percy Liang, and Luke Zettlemoyer. 2018. Quac: Question answering in context. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018*, pages 2174–2184.
- Huy Dao, Lizi Liao, Dung Le, and Yuxiang Nie. 2023. Reinforced target-driven conversational promotion. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 12583–12596.
- Yang Deng, Wenqiang Lei, Wenxuan Zhang, Wai Lam, and Tat-Seng Chua. 2022. PACIFIC: towards proactive conversational question answering over tabular and textual data in finance. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022*, pages 6970–6984.
- Xuan Long Do, Bowei Zou, Shafiq R. Joty, Anh Tran Tai, Liangming Pan, Nancy F. Chen, and Ai Ti Aw. 2023. Modeling what-to-ask and how-to-ask for answer-unaware conversational question generation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics, ACL 2023*, pages 10785–10803.
- Xuan Long Do, Bowei Zou, Liangming Pan, Nancy F. Chen, Shafiq R. Joty, and Ai Ti Aw. 2022. Cohs-cqg: Context and history selection for conversational question generation. In *Proceedings of the 29th International Conference on Computational Linguistics, COLING 2022*, pages 580–591.

- Zichu Fei, Qi Zhang, Tao Gui, Di Liang, Sirui Wang, Wei Wu, and Xuanjing Huang. 2022. CQG: A simple and effective controlled generation framework for multi-hop question generation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics, ACL 2022*, pages 6896–6906.
- Joseph L Fleiss. 1971. Measuring nominal scale agreement among many raters. *Psychological bulletin*, 76(5):378–382.
- Tianyu Gao, Xingcheng Yao, and Danqi Chen. 2021. Simcse: Simple contrastive learning of sentence embeddings. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021*, pages 6894–6910.
- Qi Gou, Zehua Xia, Bowen Yu, Haiyang Yu, Fei Huang, Yongbin Li, and Cam-Tu Nguyen. 2023. Diversify question generation with retrieval-augmented style transfer. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023*, pages 1677–1690.
- Jing Gu, Mostafa Mirshekari, Zhou Yu, and Aaron Sisto. 2021. Chaincqq: Flow-aware conversational question generation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2021*, pages 2061–2070.
- Shasha Guo, Lizi Liao, Cuiping Li, and Tat-Seng Chua. 2024a. A survey on neural question generation: Methods, applications, and prospects. *CoRR*, abs/2402.18267.
- Shasha Guo, Lizi Liao, Jing Zhang, Yanling Wang, Cuiping Li, and Hong Chen. 2024b. SGSH: stimulate large language models with skeleton heuristics for knowledge base question generation. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 4613–4625.
- Shasha Guo, Jing Zhang, Xirui Ke, Cuiping Li, and Hong Chen. 2024c. Diversifying question generation over knowledge base via external natural questions. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation, LREC/COLING 2024*, pages 5096–5108.
- Shasha Guo, Jing Zhang, Yanling Wang, Qianyi Zhang, Cuiping Li, and Hong Chen. 2022. Dsm: Question generation over knowledge base via modeling diverse subgraphs with meta-learner. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022*, pages 4194–4207.
- Shibo Hao, Yi Gu, Haodi Ma, Joshua Jiahua Hong, Zhen Wang, Daisy Zhe Wang, and Zhiting Hu. 2023. Reasoning with language model is planning with world model. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023*, pages 8154–8173.
- Tao He, Lizi Liao, Yixin Cao, Yuanxing Liu, Ming Liu, Zerui Chen, and Bing Qin. 2024. Planning like human: A dual-process framework for dialogue planning. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*, pages 4768–4791.
- Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, et al. 2024. Mixtral of experts. *arXiv preprint arXiv:2401.04088*, pages 1–13.
- Levente Kocsis and Csaba Szepesvári. 2006. Bandit based monte-carlo planning. In *Proceedings of the 17th European Conference on Machine Learning, ECML 2006*, volume 4212, pages 282–293.
- Jinggui Liang, Lizi Liao, Hao Fei, and Jing Jiang. 2024. Synergizing large language models and pre-trained smaller models for conversational intent discovery. In *Findings of the Association for Computational Linguistics, ACL 2024*, pages 14133–14147.
- Yuanyuan Liang, Jianing Wang, Hanlun Zhu, Lei Wang, Weining Qian, and Yunshi Lan. 2023. Prompting large language models with chain-of-thought for few-shot knowledge base question generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023*, pages 4329–4343.
- Lizi Liao, Grace Hui Yang, and Chirag Shah. 2023. Proactive conversational agents in the post-chatgpt world. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2023*, pages 3452–3455.
- Yanxiang Ling, Fei Cai, Jun Liu, Honghui Chen, and Maarten de Rijke. 2023. Generating relevant and informative questions for open-domain conversations. *ACM Trans. Inf. Syst.*, 41(1):1–30.
- Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegrefe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, Sean Welleck, Bodhisattwa Prasad Majumder, Shashank Gupta, Amir Yazdanbakhsh, and Peter Clark. 2023. Self-refine: Iterative refinement with self-feedback. In *Proceedings of 37th Conference on Neural Information Processing Systems, NeurIPS 2023*, pages 1–54.
- Jekaterina Novikova, Ondrej Dusek, Amanda Cercas Curry, and Verena Rieser. 2017. Why we need new evaluation metrics for NLG. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017*, pages 2241–2252.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics, ACL 2002*, pages 311–318.

- Siva Reddy, Danqi Chen, and Christopher D. Manning. 2019. Coqa: A conversational question answering challenge. *Trans. Assoc. Comput. Linguistics*, 7:249–266.
- Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik R Narasimhan, and Shunyu Yao. 2023. Reflexion: Language agents with verbal reinforcement learning. In *Proceedings of the 37th Conference on Neural Information Processing Systems, NeurIPS 2023*, pages 1–19.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V. Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2023. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations, ICLR 2023*, pages 1–24.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. 2022. Chain-of-thought prompting elicits reasoning in large language models. In *Proceedings of the 36th Conference on Neural Information Processing Systems, NeurIPS 2022*, pages 1–14.
- Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan. 2023. Tree of thoughts: Deliberate problem solving with large language models. In *Proceedings of the 37th Conference on Neural Information Processing Systems, NeurIPS 2023*, pages 1–14.
- Xiao Yu, Maximillian Chen, and Zhou Yu. 2023. Prompt-based monte-carlo tree search for goal-oriented dialogue policy planning. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023*, pages 7101–7125.
- Hongwei Zeng, Bifan Wei, Jun Liu, and Weiping Fu. 2023. Synthesize, prompt and transfer: Zero-shot conversational question generation with pre-trained language model. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics, ACL 2023*, pages 8989–9010.
- Shun Zhang, Zhenfang Chen, Yikang Shen, Mingyu Ding, Joshua B. Tenenbaum, and Chuang Gan. 2023. Planning with large language models for code generation. In *Proceedings of the Eleventh International Conference on Learning Representations, ICLR 2023*, pages 1–28.
- Zirui Zhao, Wee Sun Lee, and David Hsu. 2023. Large language models as commonsense knowledge for large-scale task planning. In *Proceedings of 37th Conference on Neural Information Processing Systems, NeurIPS 2023*, pages 1–21.

## A Experiment

### A.1 Experimental Implementation Details

**Parameters.** We configure the number of possible actions  $k$  for each node to be 5, set the number of simulations to 10, and assign the exploration weight  $w$  to 1. For both open-source and closed-source LLMs used, we set  $n$  to 1, the *temperature* to 0.7, and *top\_p* to 1.

**Prompt for Response Generation.** To guide LLMs in generation, we provide prompts. Instead of meticulously designing these, we focus on ensuring they effectively convey the intended meaning. As illustrated in Figure 3, we present the prompt used in this work for generating the response.

**Prompt for Reflection Generation.** Reflection aims to provide feedback on the entire planning path, enabling continuous self-assessment and adjustments to achieve the specified outcome successfully. Similar to the prompt for generating responses, we provide them casually rather than meticulously crafting them. Figure 4 illustrates the prompt we utilized to generate the reflection.

**Prompt for Refining Response via Feedback.** Our proposed reflection mechanism produces insightful feedback for each action along the entire planning path. This feedback is subsequently used to formulate prompts for the LLMs, thereby enhancing their responses. Similarly, we casually provide the prompts rather than crafting them meticulously. As shown in Figure 6, we present the prompt for refining response generation.

### A.2 Human Evaluation Scoring Guidelines

We detail our scoring method used to guide three annotators in evaluating the generated responses based on two key criteria: Coherence and Effectiveness. Each criterion is scored on a scale of 0, 1, or 2, with higher scores indicating better performance. These criteria are explained in more detail in Section 5.1 and illustrated in Figure 7. Coherence assesses the logical flow and relevance of responses, whereas Effectiveness measures their success in achieving the specified outcome. This methodical approach ensures a consistent and unbiased assessment of response quality.

### A.3 Sensitivity Study

We investigate the effect of varying the number of testing simulations on the performance of PC-QPR. As illustrated in Figure 5, the Success Rate of

### Prompt for Response Generation

Based on the provided **context**, **conversational history**, and **target conversation**, please generate the **follow-up question-answer pairs**. These should logically and fluently build upon the existing conversational history and the final question-answer, ensuring a smooth and logical progression.

**Context:** [Context] \n  
**Conversational History:** [Q] [A] ... \n  
**Follow-up Question-Answer Pairs:** {Q} {A} ... \n  
**Target Question-Answer Pair:** [Q] [A]

Figure 3: The prompt for response generation.

### Prompt for Reflection Generation

Please act as an experienced conversation analyst and provide specific suggestions for significantly improving the 'generated question-answer pairs'. Your analysis should focus on the following two aspects for each pair:\n

1. Coherence: For each question-answer pair, evaluate whether the content aligns with the given conversation history and the described **context's** story plot. Assess if each pair contributes to the logical coherence of the entire conversation, including the **conversation history**, the **generated conversation**, and the **target conversation**, with each turn elaborating on a specific plot element from the context for a smooth overall flow.\n
2. Effectiveness: Analyze whether each question-answer pair naturally transitions into the subsequent part of the conversation and reaches the predefined target question-answer pair.\n

**Context:** [Context] \n  
**Conversational History:** [Q] [A] ... \n  
**Generated Question-Answer Pairs:** [Q] [A] ... \n  
**Target Question-Answer Pair:** [Q] [A] \n  
**Feedback:** {Feedback}

Figure 4: The prompt for reflection generation.

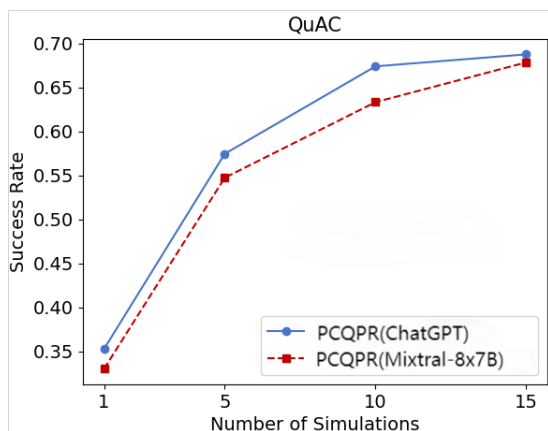


Figure 5: Sensitivity study.

PCQPR on QuAC varies with the number of simulations, showing an initial increase in performance

### Prompt for Refining Response

Please act as an experienced conversation analyst and refine the '**previously generated question-answer pairs**' based on the provided **feedback** to align them with the given **conversation history** and the described **context's** story plot. Ensure that the entire conversation--including the conversation history, **refined question-answer pairs**, and the **target conversation**--is logically coherent, with each turn elaborating on a specific plot element from the context, thus ensuring a smooth overall flow.

**Context:** [Context] \n  
**Conversational History:** [Q] [A] ... \n  
**Generated Question-Answer Pairs:** [Q] [A] ... \n  
**Feedback:** [Feedback] \n  
**Target Question-Answer Pair:** [Q] [A] \n  
**Refined Question-Answer Pairs:** {Q} {A} ... \n

Figure 6: The prompt for refining response generation involves obtaining detailed feedback from LLMs.

### Scoring Guidelines

#### Coherence

**Score 0:** The generated response is entirely irrelevant to the context and logically incoherent with the entire conversation.

**Score 1:** The generated response is partially relevant to the context yet shows lapses in logical coherence, resulting in only partial alignment with the conversation.

**Score 2:** The generated response is fully relevant to the context and demonstrates complete logical coherence, seamlessly integrating into the conversation.

#### Effectiveness

**Score 0:** The generated response is completely unlikely to achieve the predefined outcome.

**Score 1:** The generated response moderately aligns with the predefined outcome but may not comprehensively address all intended aspects.

**Score 2:** The generated response is highly likely to achieve the predefined outcome, aligning closely with all specified criteria.

Figure 7: Human evaluation scoring guidelines for two criteria: Coherence and Effectiveness.

followed by a more gradual and steady increase upon reaching 10 simulations. In our experiments, we set the number of simulations to 10 to balance the performance gains against the associated costs. Beyond this threshold, while performance may continue to improve, the rate of increase slows significantly, indicating diminishing returns. Therefore, setting the number of simulations to 10 represents an optimal compromise between achieving substantial performance improvements and maintaining reasonable cost efficiency.

Context	Conversation	Generated Responses by Our Proposed PCQPR(GPT-4-Turbo)
<p>Alvarez said, "I think of myself as having had <b>two separate careers, one in science and one in aviation.</b>" ... <b>During World War II he led the development of multiple aviation-related technologies...</b> Later in his career <b>Alvarez served on multiple high level advisory committees related to civilian and military aviation.</b> These included <b>a Federal Aviation Administration task group on future air navigation and air traffic control systems,</b> ...</p>	<p><b>Path Flow:</b> ① <i>Initial</i> ② <i>Follow-up</i> ③ <i>Conclusion</i></p> <p>① Did Alvarez fly as his career? Two careers, one in science and one in aviation.</p> <p>② What were some of his careers that involved flying? During World War II he led the development of multiple aviation-related technologies.</p> <p>② What else interesting happened with him in aviation? Alvarez served on multiple high level committees related to civilian and military aviation.</p> <p>③ What were his duties on that committee? A Federal Aviation Administration task group on future air navigation and air traffic control systems.</p>	<p>What specific aviation-related technologies did Alvarez help develop during World War II? During World War II, Alvarez led the development of multiple aviation-related technologies.</p> <p>What were some of the advisory roles Alvarez held in relation to aviation? Alvarez served on multiple high-level advisory committees.</p> <p>On which committees did Alvarez serve in the aviation? A Federal Aviation Administration task group on future air navigation and air traffic control systems.</p>
<p>In September 2009, <b>eight years after Phillips's death, his eldest daughter Mackenzie claimed that she and her father had a 10-year incestuous relationship.</b> <b>Mackenzie wrote of the relationship, which she said began when she was 19 years old in 1979,</b> in her memoir <i>High on Arrival</i>. Mackenzie wrote that <b>the relationship began after Phillips raped her while they were both under the influence of heavy narcotics on the eve of her first marriage.</b> <b>Mackenzie Phillips appeared on The Oprah Winfrey Show on September 23, 2009,</b> and told Winfrey that her father injected her with cocaine and heroin. ...</p>	<p>① What are the incest allegations? Eight years after Phillips's death, his eldest daughter Mackenzie claimed that she and her father had a 10-year incestuous relationship.</p> <p>② Were these claims true? Mackenzie wrote of the relationship, which she said began when she was 19 years old in 1979.</p> <p>② How did it begin? The relationship began after Phillips raped her while they were both under the influence of heavy narcotics on the eve of her first marriage.</p> <p>③ Are there any other interesting aspects about this article? Mackenzie Phillips appeared on The Oprah Winfrey Show on September 23, 2009.</p>	<p>When did Mackenzie Phillips start the incestuous relationship with her father? She claimed it began when she was 19.</p> <p>How did Mackenzie Phillips describe this start? She was raped under the influence of heavy narcotics before her marriage.</p> <p>How did the public learn about Mackenzie Phillips's allegations against her father? Mackenzie Phillips revealed the allegations in her memoir "High on Arrival" and discussed them on The Oprah Winfrey Show on September 23, 2009.</p>
<p><b>Gaynor was romantically involved with her friend and frequent co-star, Charles Farrell, during the time of their work together in silent film, until she married her first husband.</b> Choosing to keep their relationship out of the public eye, Gaynor and Farrell were often assisted by mutual friend <b>Douglas Fairbanks Jr.</b> in maintaining the ruse. ... <b>Gaynor was married three times and had one child.</b> ... <b>On August 14, 1939, she married MGM costume designer Gilbert Adrian in Yuma, Arizona.</b> This relationship has been called a lavender marriage, since <b>Adrian was openly gay within the film community while Gaynor was rumored to be gay or bisexual.</b> ...</p>	<p>① Who was Janet Gaynor romantically involved? Gaynor was romantically involved with her friend and frequent co-star, Charles Farrell.</p> <p>① How many times did Janet Gaynor marry? Gaynor was married three times and had one child.</p> <p>② Who did Janet Gaynor marry the first time? Douglas Fairbanks Jr.</p> <p>② Who did Janet Gaynor marry in 1939? On August 14, 1939, she married MGM costume designer Gilbert Adrian in Yuma, Arizona.</p> <p>③ Why was Janet Gaynor marriage to Gilbert Adrian was called a lavender marriage? Adrian was openly gay within the film community while Gaynor was rumored to be gay or bisexual.</p>	<p>To whom was Janet Gaynor's first marriage? Douglas Fairbanks Jr.</p> <p>When did Janet Gaynor and Gilbert Adrian get married? On August 14, 1939</p> <p>What was the nature of Janet Gaynor's marriage to Gilbert Adrian, and how was it perceived within the film community? Janet Gaynor's marriage to Gilbert Adrian was called a lavender marriage, as Adrian was openly gay within the film community while Gaynor was rumored to be gay or bisexual.</p>

Figure 8: Case studies for three examples generated by our method, PCQPR(GPT-4-Turbo).

#### A.4 Case Studies

To visualize our model's performance, Figure 8 presents three examples generated by PCQPR (GPT-4-Turbo). These examples demonstrate the model's ability to proactively steer the generation process to achieve the specified outcome. This

showcases the model's advanced understanding and manipulation of context, ensuring that each QA pair is not only relevant but also precisely aligned with the desired outcome.