Multi-User Chat Assistant (MUCA): a Framework Using LLMs to Facilitate Group Conversations

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Abstract

Recent advancements in large language models (LLMs) have provided a new avenue for chatbot development, while most existing research has primarily centered on single-user chatbots that focus on deciding "What" to answer after user inputs. In this paper, we identified that multi-user chatbots have more complex 3W design dimensions - "What" to say, "When" to respond, and "Who" to answer. Additionally, we proposed Multi-User Chat Assistant (MUCA), which is an LLM-based framework for chatbots specifically designed for group discussions. MUCA consists of three main modules: Sub-topic Generator, Dialog Analyzer, and Utterance Strategies Arbitrator. These modules jointly determine suitable response contents, timings, and the appropriate recipients. To make the optimizing process for MUCA easier, we further propose an LLM-based Multi-User Simulator (MUS) that can mimic real user behavior. This enables faster simulation of a conversation between the chatbot and simulated users, making the early development of the chatbot framework much more efficient. MUCA demonstrates effectiveness, including appropriate chime-in timing, relevant content, and positive user engagement, in goal-oriented conversations with a small to medium number of participants, as evidenced by case studies and experimental results from user studies.

1 Introduction

In recent years, the field of chatbot research has experienced a surge in interest and advancements. Large language models (LLMs) like GPTs (OpenAI, 2023; Brown et al., 2020; Radford et al., 2019a) have emerged as a powerful tool for developing chatbots. Profound research is being conducted on pre-training or fine-tuning LLMs for task-oriented dialogue systems (Su et al., 2021; He et al., 2022a). While there is an increasing number

of chatbots designed for single-user interactions, research on chatbots for group conversations remains limited. This hinders the direct application of LLM-based chatbots in group conversation scenarios, including steering meetings, hosting brainstorming sessions, and directing debate events.

This paper presents Multi-User Chat Assistant (MUCA), an LLM-based framework for group conversation chatbots which, as far as the authors are aware of, is the first LLM-based framework dedicated to multi-user conversations. The framework is composed of three modules that utilize LLMs with specially crafted prompts. These modules, namely Sub-topic Generator, Dialog Analyzer, and Utterance Strategies Arbitrator, work in harmony to enable efficient and appropriate participation in group conversations. Unlike single-user chatbots that simply determine "What" to answer after user inputs, multi-user chatbots have 3W (What, When, Who) design dimensions that we identified to appropriately determine not only "What" to answer, but also "When" to answer and "Who" to answer. We demonstrate that many of the challenges, such as advancing stuck conversation and managing multi-threaded discussion, that a multiuser chatbot performs can be mapped to these dimensions, and we also provide a set of capabilities that we implement with our proposed framework. To enable fast iteration and development of the proposed MUCA framework, we also formulate an LLM-based Multi-User Simulator (MUS) that improves over time with human-in-the-loop feedback.

The effectiveness of the proposed MUCA framework has been demonstrated through both case studies and user studies. The MUCA is not only quantitatively evaluated through calculations of user engagement, conversation evenness, and opinion consensus, but also subjectively evaluated by users from the perspectives of efficiency, conciseness, and usefulness. From the obtained experimental results, we can find the proposed MUCA framework

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can usually outperform a baseline framework. The highlights of our work are as follows.

- We propose an LLM-based Multi-user Chat Assistant (MUCA) framework based on the 3W (What, When, Who) design dimensions. MUCA consists of three key modules: Subtopic Generator, Dialog Analyzer, and Utterance Strategies Arbitrator. These modules collaborate to perform tasks that enhance the multi-user chat experience.
- We propose an LLM-based user simulator (MUS) to facilitate the optimizing process for MUCA. MUS is programmed to mimic real user behavior, enabling the simulation of a dialogue as multiple agents interact with each other by incorporating the "human-inthe-loop" concept.
- We provide an in-depth evaluation of MUCA using case studies and user studies in various discussion tasks and group sizes. Our proposed MUCA significantly improves over a baseline chatbot in goal-oriented communication tasks such as decision-making, problemsolving, and open discussions. User studies revealed a strong preference for MUCA over the baseline chatbot in enhancing chatting efficiency and facilitating brainstorming sessions.

The rest of this paper is organized as follows. In Section 2, we review the prior research in single-user and multi-user chatbots including reinforcement learning and LLMs. In Section 3, we firstly propose 3W (What, When, Who) design dimensions and then dive into the details of the MUCA framework and MUS design. In Section 4 through case studies and user studies, we showcase the effectiveness of MUCA in handling group chats of varying sizes and with different discussion tasks. This is followed by limitation and future work discussion in Section 5. We conclude this paper in Section 6.

2 Related Work

In recent years, there has been a surge of interest in chatbot research. Integration of reinforcement learning (RL) techniques into chatbot has been studied extensively (Tran and Le, 2023; Li et al., 2016; Sankar and Ravi, 2019; Jhan et al., 2021; Hancock et al., 2019; See and Manning, 2021; Thosani et al., 2020; Kim et al., 2020b; Su et al., 2015; Kreutzer et al., 2021; Jaques et al., 2019; Kwan et al., 2023; Graßl, 2019). The RL process focuses on an agent

analyzing user responses, identifying positive signals, and recognizing behavioral patterns. By learning from diverse interactions, the agent develops policies that guide situation-dependent behavior. Deep RL methods such as Q-learning, DQN, policy gradient, and off-policy reinforce improve performance (Yu et al., 2016, 2017; Papaioannou et al., 2017; Li et al., 2018; Williams and Zweig, 2016; Serban et al., 2017). However, training data is limited due to the need for human involvement. Conversely, recent advancements in LLMs, particularly with the emergence of GPT-4 (OpenAI, 2023), offer a novel approach to developing chatbots. However, without appropriate "prompts", these models may exhibit unintended behaviors, such as fabricating facts, producing biased or harmful text, or not adhering to user instructions (OpenAI, 2023; Tamkin et al., 2021; Markov et al., 2023). To address these issues, our proposed MUCA framework utilizes hierarchical prompting and chain-of-thoughts (Wei et al., 2022), detailed in Section 3.

Conversational models with LLMs can generally be classified into two categories: open-domain and task-oriented models (Young et al., 2013; Budzianowski and Vulić, 2019). Open-domain models are typically trained to respond appropriately to a wide range of input contexts, resulting in an agent capable of interacting with users in diverse scenarios. On the other hand, task-oriented models are specifically designed to assist users in accomplishing certain goals.

Open-Domain Models: LLMs have demonstrated remarkable performance across various tasks. They are typically pre-trained on large amounts of data and fine-tuned with human-curated data through supervised learning and reinforcement learning approaches. Some of the recent work including GPT models (OpenAI, 2023; Ouyang et al., 2022; Brown et al., 2020; Radford et al., 2019b), LLaMa2 (Touvron et al., 2023), PaLM2 (Anil et al., 2023), Bloom (Scao et al., 2022) and LaMDa (Thoppilan et al., 2022). Some of the recent versions of these models, such as GPT-4, have shown promising results as conversational agents. Despite the overall good performance of these models across multiple tasks on text generation, there are still continuing efforts to improve them for specific scenarios (Chen et al., 2021; Wu et al., 2023b).

Task-Oriented Dialogue Models: Fine-tuning or pre-training LLMs for task-oriented dialogue systems has been studied extensively. For exam-

ple, (Budzianowski and Vulić, 2019; Hosseini-Asl et al., 2020; Yang et al., 2021) fine-tuned GPT-2 on dialogue data as conversational models. (Su et al., 2021) reformulated the sub-tasks of taskoriented dialogue as text-to-text tasks and presented a new model called PPTOD, by pre-training the T5 model on a unified multi-turn dialogue corpora. (Wang et al., 2022a) introduced additional modules to GPT-2 to achieve better performance on transfer learning and dialogue entity generation. (He et al., 2022b) proposed the GALAXY model, which incorporates dialogue policy knowledge into model pre-training through semi-supervised learning. (He et al., 2022a) presented SPACE2 trained on limited labeled and large amounts of unlabeled dialogue data using semi-supervised contrastive pre-training. Our MUCA framework is based on prompting methods without the need for model training and data collection. It is task-oriented but not limited to closed-domain knowledge.

Prompting has been one of the most effective methods for enhancing LLMs performance. (Wei et al., 2022; Wang et al., 2022b; Yao et al., 2023; Wang et al., 2023) presented methods such as chainof-thoughts, self-consistency, and tree of thoughts prompting framework to instruct LLMs in enhancing their thinking and planning processes. This, in turn, improves the quality and accuracy of the model's responses. (Lu et al., 2023; Lewis et al., 2020) proposed a framework for retrieving external knowledge as part of the prompt to expand or update LLMs' knowledge base to answer questions more accurately. (Wu et al., 2023a; Liang et al., 2023) proposed a multi-agent framework that deployed multiple LLMs as agents to collaboratively solve tasks. In (Lee et al., 2023), a modular prompted chatbot, utilizing LLMs and incorporating techniques such as chain-of-thoughts, few-shot learning, and memory storing, was proposed to facilitate long open-domain conversations. Our proposed MUCA framework incorporates several prompting techniques, including chain-of-thoughts and zero-shot learning, to effectively comprehend user intent and generate accurate utterances.

User Simulator: The majority of prior research has focused on creating a user simulator to engage with the system or environment. This simulator is used to collect an extensive array of simulated user experiences. There are two primary approaches: agenda-based and data-driven (Kwan et al., 2023). The agenda-based simulator main-

tains a user agenda stack with all the necessary information following pre-defined rules (Schatzmann et al., 2007). Using a sequence-to-sequence framework, the data-driven simulator generates user responses based on the given dialogue context (Schatzmann et al., 2006). Creating user simulators involves various methods, but evaluating their quality is challenging as it's hard to accurately reflect user behavior. We implemented a data-driven user simulator (MUS) for MUCA to generate diverse simulated user utterances.

Multi-user Conversational Model: The majority of chatbot research primarily concentrates on single-user interactions, characterized by welldefined conversation structures that consist of adjacency pairs (Schegloff, 1968), which guide the timing and content of the chatbot's responses. Besides, it is common for chatbots to respond by asking the user questions and steering the conversation in various directions in the single-user setting, a concept known as mixed initiative (Walker and Whittaker, 1990). However, in multi-user environments, mixed initiative often leads to uneven participation and inefficient discussion, as the conversation tends to oscillate between only a few participants or, in some cases, just one participant and the chatbot. Designing chatbots for multi-user scenarios presents a more significant challenge, as the design paradigm must not only determine the response content but also the proper timing and intended recipient of the response. Despite the complexity, there have been a limited number of studies exploring multi-user scenarios, with some focusing on the development of effective communication strategies. (Do et al., 2022) proposed communication strategies for balanced participation, (Wagner et al., 2022) proposed four moderation strategies for planning and negotiating joint appointments. (Kim et al., 2020a) proposed four features, such as organizing members' opinions, to facilitate group chat discussion. Our proposed MUCA framework aims to interact with multiple users in a single dialogue session. The focus is on creating a framework that enables existing LLMs to function effectively in multi-user scenarios.

3 Multi-User Chat Assistant (MUCA) Framework

In this section, we begin with a discussion on 3W (What, When, Who) design dimensions for multiuser chatbots. We then describe some of the chal-

lenges our proposed chatbot aims to overcome, and how these challenges relate to the 3W dimensions. Next, we dive into the details of the major modules of our proposed Multi-User Chat Assistant (MUCA) framework. We also introduce our LLM-based user simulator (MUS), which can mimic human behaviors in multi-user experimentation, allowing us to iterate MUCA more efficiently.

3.1 Design Dimensions and Challenges

Tasks considered in this paper are neither required nor exhaustive, and can be very different from diverse roles that a chatbot assumes. In this study, we focus on a multi-user chatbot that serves as a supportive assistant, similar to previous rule-based multi-party/multi-user chatbots designed to facilitate group interactions (Cranshaw et al., 2017; Avula et al., 2018; Toxtli et al., 2018).

3.1.1 3W Design Dimensions

Design considerations for chatbots can vary significantly based on the specific scenarios and requirements. A chatbot developed for a single-user setting may differ substantially from one designed for multi-user chats. Similarly, a chatbot designed to facilitate official meetings might be quite distinct from one intended for casual conversations. Nevertheless, despite these varying scenarios, we believe that most design factors can be categorized under one or more of the three "W" dimensions, or 3W (What, When, Who) dimensions, which we elaborate further in this section.

Conversations involving a single user typically exhibit a well-defined structure, such as adjacency pairs – each being two consecutive utterances with the first one anticipating a specific response from the second one (Schegloff, 1968). Examples include questions expecting answers and proposals anticipating acceptance or rejection. This type of structure significantly alleviates the design burden of single-user chatbots as it can help instruct the timing and the content of chatbots' subsequent responses. Thus, the primary metric for designing single-user chatbots has often focused on the quality of their responses, or "What" in the 3W dimensions (Yu et al., 2016, 2017; Tran and Le, 2023).

Designing chatbots for multiple users is generally more challenging than for a single user, which can be considered as a special case of the multiuser scenario. In the context of a multi-user chat scenario, the design paradigm must not only determine the content of the response ("What"), but also

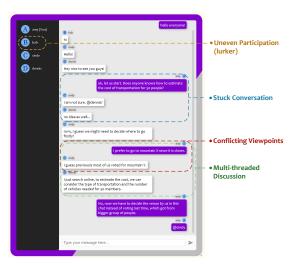


Figure 1: An example snippet for a group chat. Four key challenges are shown in this multi-user environment: uneven participation, stuck conversation, conflicting viewpoints, and multi-threaded discussions.

the appropriate timing of the response ("When") and the intended recipient of the response ("Who"). These 3W dimensions are elaborated as follows:

- Content Intelligence ("What"): Determining what to respond is very important in the design of both single-user and multi-user chatbots. However, this dimension is considerably more complex for a multi-user chatbot, as it may need to manage tasks such as conflict resolution, multi-threaded discussions with multiple users, and uneven participation. These tasks are less frequently encountered or are easier to handle for single-user chatbots.
- Timing Intelligence ("When"): Unlike the case in a single-user setting where the chatbot usually responds after every user input, a multi-user chatbot needs to exhibit appropriate timing. Therefore, a decision-making process is needed to determine the right timing to chime in or keep silent, thereby avoiding over-responding and insufficient engagement.
- Recipient Intelligence ("Who"): A multiuser chatbot should have a decision-making mechanism, which could leverage the analysis of the conversation records, to determine the recipient of its responses, such as a specific group of participants, unspecified participants, or all participants.

3.1.2 Design Challenges

While chatbots with different purposes face various challenges and tasks, we believe that most of these

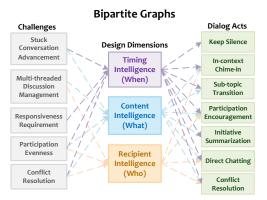


Figure 2: Bipartite relation graphs between challenges, design dimensions, and designed dialog acts.

can be mapped onto at least one of the three "W" design dimensions. This study aims to create a framework for multi-user chatbots, which can be applied to various real-world tasks. Here, we list some of the challenges that our framework attempts to address (as shown in Figure 1), and how they are associated with the 3W dimensions (as shown in Figure 2). As we will see later in the paper, some tasks, which are simpler in single-user cases, can be far more complex in multi-user scenarios.

- Stuck Conversation Advancement: It is closely related to the dimensions of "When" and "What". If a conversation is stuck and cannot progress due to reasons like participants requiring suggestions, MUCA can identify this and chime in appropriately. Refer to the area outlined in blue in Figure 1 as an illustration.
- Multi-threaded Discussion Management: It is closely related to "What" and "Who" dimensions. MUCA can handle chats with multi-threaded discussions, where multiple topics may overlap along the timeline. Handling such discussions in multi-user chat scenarios can be challenging as the chatbot needs to keep track of the topics under discussion, and at the same time identify the participants who are involved in each topic. Refer to the area outlined in green in Figure 1 as an illustration.
- Responsiveness Requirement: It is particularly related to "When" dimension, since the capability of responding in a timely manner is essential to perform many time-sensitive tasks. Responsiveness in multi-user conversations is far more challenging than in single-user cases due to the increased demand for computational resources. MUCA is able to

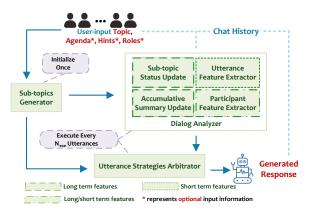


Figure 3: Multi-user Chat Assistant (MUCA) framework architecture.

- effectively manage the higher message traffic, complex interactions from multiple users, and multi-threaded discussions.
- Participation Evenness: In the proposed chatbot design, we also consider encouraging even participation, which is relevant to all 3W dimensions. MUCA is designed to identify inactive users, determine the appropriate timing for intervention, and utilize suitable, customized, and non-offensive language to encourage participation. Refer to the area outlined in yellow in Figure 1 as an illustration.
- Conflict Resolution: It is related to all *3W* dimensions. MUCA is capable of offering recommendations and summarization to assist participants in reaching an agreement during voting, resolving disputes, or concluding long-lasting discussions on a particular issue. Refer to the area outlined in red in Figure 1 as an illustration.

MUCA is a general framework design in which capabilities can be added or removed by modifying the Dialog Analyzer and Utterance Strategies Arbitrator to meet other design requirements and scenarios. In the next section, we will describe the framework for MUCA, detailing each major module of the architecture and how they contribute to addressing challenges that were mentioned previously in this section.

3.2 Framework Architecture

Figure 3 illustrates the framework architecture and information flow, which consists of three major modules: (1) Sub-topics Generator, which generates the initial sub-topics. (2) Dialog Analyzer, which extracts short-term and long-term features from chat history (3) Utterance Strategies Arbitra-

Algorithm 1 MUCA

```
Require: Input I, pre-defined N_{exe}, LLM gener-
   ator p_{\theta}, short-term window size N_{sw}, warm-up
   turns W, cool-down turns C, trigger conditions
   f, rank function g, user message u_{m,i} at time i.
   T \sim \bar{p}_{\theta}(T|I)
   i \leftarrow 0, j \leftarrow 0, n \leftarrow 0
   while do
         if n = N_{exe} then
               ts_{j+1}, t_{j+1} \sim \bar{p}_{\theta}^{CoT}(ts_{j+1}, t_{j+1}|I, t_{j}, ts_{j}, U_{N_{sw}, i})
               T_d \sim \bar{p}_{\theta}(T_d|T, U_{N_{sw},i})
               s_{j+1} \sim \bar{p}_{\theta}(s_{j+1}|T_d, s_j, U_{N_{sw},i})
               Stat_p \leftarrow \{freq, len, N_{ed}, N_{inq}\}
               Cond \leftarrow f(t_{j+1}, s_{j+1}, U_{N_{sw},i},
                                  T_d, Stat_p
               rank_{j+1} \leftarrow g(Cond, W, C, U_{N_{sw}, i})
               act_{j+1} \leftarrow \arg\min rank_{j+1}

r_{j+1} \sim \bar{p}_{\theta}^{CoT}(r_{j+1}|act_{j+1},s_{j+1},
                                  U_{N_{sw},i}, t_{j+1}, I, T_d, Stat_p)
               u_{i+1} \leftarrow r_{j+1}
               n \leftarrow 1
               j \leftarrow j + 1
         else
               u_{i+1} \leftarrow u_{m,i+1}
               n \leftarrow n + 1
         end if
         i \leftarrow i + 1
   end while
```

tor, which determines the dialog acts corresponding to our design dimensions, which are outlined in Figure 2. In accordance with the framework, the complete algorithm can be found in Algorithm 1^1 . Overall, the Sub-topics Generation is executed once, and the Dialog Analyzer and Utterance Strategies Arbitrator are executed sequentially for every N_{exe} utterances, which ensures the latency-efficiency in front of the higher message traffic and complex interactions from multiple users. The following sub-sections provide an in-depth explanation of each module.

Throughout this paper, we use p_{θ} to denote a pre-trained LLM with parameter θ , p_{θ}^{CoT} to represent p_{θ} integrated with the Chain-of-Thoughts (CoT) methods (Wei et al., 2022), I and T to indi-

cate user-input information and derived sub-topics, and u, t, s to signify users' utterances (including MUCA's responses), the status of T, and summaries of the utterances, respectively. For simplicity, we use $y \sim \bar{p}_{\theta}(y|v_1,v_2,\dots)$ to denote that we sample and post-process from the LLM pdf p_{θ} (·|prompt $_y(v_1,v_2,\dots)$) to get the output y, given v_k as the input to a prompt template for generating output y. We use $U_{N,i}$ to represent users' utterances within N window size at the time stamp i, i.e., $\{u_{i-N+1},\dots,u_i\}$. N_p represents the total number of participants in the group chat.

3.2.1 Sub-topic Generator

This module initializes a set of relevant sub-topics, T, pretraining to the primary subject in user-input information I: $T \sim \bar{p}_{\theta}(T|I)$. User-input information I includes a topic and may optionally include an agenda, hints, and attendee roles. Hints represent any supplementary details users wish to emphasize, while attendee roles refer to the positions designated to participants. The integration of relevant hints and attendee roles has demonstrated success in generating fewer arbitrary and random sub-topics. Consequently, this module enables the MUCA to seamlessly navigate and engage in conversations based on these derived sub-topics. The prompts are documented in Appendix A.2.1.

3.2.2 Dialog Analyzer

The major task of the Dialog Analyzer is to extract and update useful long-term and short-term signals to help the Utterance Strategies Arbitrator module determine the appropriate dialog acts for the response. It consists of the following sub-modules:

Sub-topic Status Update: This sub-module effectively updates the status of individual subtopic, which are defined in terms of discussion progress: not discussed, being discussed and well discussed. The statuses are initialized by not discussed for each sub-topic. To update the statuses, the prompting utilizes CoT style, which firstly generates the topic summaries ts_{j+1} using the userinput information I, the previous topic summary ts_j and short-term context window with a size of N_{sw} : $ts_{j+1} \sim \bar{p}_{\theta}(ts_{j+1}|I,U_{N_{sw},i},ts_j)$. Then, the statuses of the sub-topics are updated as follows: $t_{j+1} \sim \bar{p}_{\theta}^{CoT}(t_{j+1}|t_j,ts_{j+1},U_{N_{sw},i})$. The full prompts, detailed description, and data flow are shown in Appendix A.2.2.

Utterance Feature Extractor: This sub-module extracts all $being\ discussed$ sub-topics T_d from

¹This algorithm is slightly different from its actual implementation, where act_{j+1} Direct Chatting takes place immediately if a keyword @mubot is matched in the participant's utterance, see in Appendix A.1. The details of Direct Chatting can be found in Section 3.2.3

the short-term context window with a size of N_{sw} given all possible sub-topics T: $T_d \sim \bar{p}_{\theta}(T_d|T,U_{N_{sw},i})$ where $T_d \subset T$. This enables MUCA to keep track of the current sub-topics especially for the scenario of multi-threaded discussion mentioned in Section 3.1, which are then passed to Utterance Strategies Arbitrator to generate appropriate results.

Accumulative Summary Update: This submodule updates the summary for each participant across various sub-topics based on the long-term context window². It takes into account sub-topics T_d (being discussed), previous summary s_j and the short-term context window with a size of N_{sw} : $s_{j+1} \sim \bar{p}_{\theta}(s_{j+1}|T_d,s_j,U_{N_{sw},i})$. The updated summary is subsequently fed back into the current submodules (sub-topic status update and accumulative summary update) for further refinements in the next round. Additionally, it is utilized by downstream modules to generate suitable responses. More descriptions are shown in Appendix A.2.2.

Participant Feature Extractor: Unlike the above LLM-based sub-modules, this sub-module extracts statistical features, which include chime-in frequency freq, chime-in utterance total length lenfor each participant from both long-term context window with a size of N_{lw} and short-term context window with a size of N_{sw} . Additionally, the proposed participant feature extractor measures the frequency at which each participant chimes in on different sub-topics, effectively documenting their degree of interest in those specific areas. This serves as a reference for customizing encouragement to increase lurkers' participation – details are discussed in the next sub-section. These statistical data are utilized in a downstream sub-module (participation encouragement) to identify participants who play a passive role in group interactions, and then provide customized encouragement for them to speak up. This sub-module also records the number of participants who discussed the sub-topic from the beginning N_{ed} and the number of participants who are still discussing under the short-term context window N_{inq} . These data serve as signals

for *sub-topic transition* in the next sub-section.

3.2.3 Utterance Strategies Arbitrator

As shown in Figure 2, we have implemented seven dialog acts in Utterance Strategies Arbitrator, which serves as the gateway for MUCA to communicate with participants. All dialog acts contribute collaboratively to the proposed design dimensions for multi-user chatbots, as outlined in Section 3.1. The rank of the dialog acts is designed heuristically and determined dynamically by a set of trigger conditions for dialog acts Cond, a set of warm-up turns W and a set of cool-down turns $C: rank_{j+1} \leftarrow g(Cond, W, C, U_{N_{sw},i})$. The default ranking of triggered dialog acts aligns with the order in which they are presented below and the highest ranked dialog act act_{i+1} is chosen among all eligible dialog acts whose trigger conditions are met. The corresponding response r_{j+1} are generated based on current summary s_{j+1} , the short-term context window with a size of N_{sw} and other upstream signals sig_{j+1}^3 : $r_{j+1} \sim \bar{p}_{\theta}^{CoT}(r_{j+1}|act_{j+1}, s_{j+1}, U_{N_{sw},i}, sig_{j+1}).$ The signals sig_{j+1} , trigger conditions cond, warmup turns w, and cool-down turns c vary for each dialog act and are introduced below.

Direct Chatting: Participants can directly interact with MUCA, which serves as a support assistant for individual users, addressing their specific requests and providing assistance as needed. This dialog act always has the highest priority and MUCA responds immediately regardless of the execution period once a user pings the MUCA. Thus, it has no warm-up and cool-down turn, and its trigger condition is met when the keyword of @mubot (case-insensitive) is matched in the last utterance: $cond \leftarrow f(u_i)$. Many upstream features are extracted by the Dialog Analyzer and used as references for generating appropriate responses: $sig_{j+1} = \{t_{j+1}, T_d, I\}$. It is also worth mentioning that additional well-crafted prompting is required to avoid potential hallucination⁴, which is very common especially in this dialog act. Examples can be shown in Section 4.2.2. MUCA demonstrates adaptive responses to various types of requests, shown in Appendix A.2.3.

 $^{^2}$ Modern LLMs may have extensive context window sizes, with some capable of processing over 32k tokens, which allows chatbots to consider very long historical data, regardless of efficiency and cost considerations. In our experiment, we use a relatively smaller context window N_{sw} to demonstrate that the summarization feature, by design, can be achieved without feeding all chat history, and is also feasible for LLMs with relatively smaller context window sizes. More details see Appendix A.2.2.

 $^{^3}sig_{j+1}\subset\{t_{j+1},I,T_d,Stat_p\}$ varies with different act_{j+1} . For simplicity, in Algorithm 1, the superset instead of sig_{j+1} is used in the formula.

⁴When a chatbot is designed based on LLMs, the hallucination is inherited, generally causing confusion and misunderstanding for users. Without careful treatment, the chatbot might provide irrelevant or incorrect information.

Initiative Summarization: This dialog act enables the MUCA to generate a concise take-home summary from fragmented messages across various participants and sub-topics, providing a single insightful sentence for a clearer grasp of the discussion. Its trigger condition is heuristically designed for the scenarios when enough participants N_{active} actively joined discussions since the last triggering: $cond \leftarrow f(N_{active}, N_p)$. Its warm-up turn and cool-down turn depend on the number of participants N_p : $w = 11 * N_p$ and $c = 12 * N_p$, respectively. Accumulative summary update submodule periodically updates the summary using $sig_{i+1} = \{T_d\}$ and concisely presents the key takehome message, which will be displayed when it becomes the highest ranked eligible dialog act.

Participation Encouragement: This dialog act aims to engage less vocal participants and promote balanced contributions in a conversation. It utilizes statistical features derived from participant feature extractor (such as chime-in frequency freq, utterance total length len) to identify participants who have spoken very little in both long-term and shortterm context windows. The process of identifying a participant as a lurker is designed to be conservative. A participant is only considered as a lurker if their freq and len are significantly lower than the average in the long-term context window, and they have spoken very few in the short-term context window, shown in Equation 1 and 2 below. Instead of using KL divergence, which evaluates overall distribution difference, we computed a ratio related to the variance to focus on individual participant data. For conditions based on long-term features:

$$\begin{cases}
\frac{(freq^{(x)} - mean_{freq})^2}{var_{freq}} > thre_{freq} \\
\frac{(len^{(x)} - mean_{len})^2}{var_{len}} > thre_{len}
\end{cases} (1)$$

For conditions based on short-term features:

$$\begin{cases} freq^{(x)} < thre_{freq} \\ len^{(x)} < thre_{len} \end{cases}$$
 (2)

where $freq^{(x)}$, $mean_{freq}$, var_{freq} in Equation 1 denotes the chime-in frequency for participant x, frequency mean and sample variance value for all participants in the long-term window, respectively. len denotes utterance total length. $thre_{freq} = 0.4$ and $thre_{len} = 0.4$ are chosen heuristically based on experiments. Similarly, $freq^{(x)}$, $len^{(x)}$ in Equa-

tion 2 denotes features for participant x in the short-term window and we choose $thre_{freq}=1$ and $thre_{len}=5$.

Also, its warm-up turn is set as $w=3*N_p$ and the cool-down turn for each participant increases linearly when triggered each time: $c_{j+1}^{(x)}=2+c_{j}^{(x)}$. This approach ensures that users who prefer to remain silent are not constantly prompted to participate in the chat. MUCA generates personalized messages by considering the lurker's chat history and chime-in status extracted from participant features: $sig_{j+1}=\{freq_{j+1},len_{j+1}\}$. See more details and examples in the Appendix A.2.3.

Sub-topic Transition: This dialog act enables the MUCA to introduce a new and highly relevant topic when conversations reach a point where users have well-discussed the current topic or when most users are no longer interested in it. There are two trigger conditions for transitioning to a new sub-topic, $cond \leftarrow f(N_{ed}, N_{ing}, N_p)$: (1) less than half of the participants have discussed the current subtopic: $N_{ed} < N_p/2$, and (2) more than half of the participants were discussing the current subtopic, but only a few are discussing it now within a short-term context window of size N_{sw} : $N_{ed}>=N_p/2$ and $N_{ing}< N_{ed}/2.$ Its warm-up turn and cool-down turn are set as $w = 5 * N_p$ and $c = 7 * N_p$, respectively. Note that its rank is lower than Participation Encouragement since the MUCA aims to encourage inactive participants to contribute before switching to a new sub-topic using $sig_{j+1} = \{N_{ed}, N_{ing}\}$. Introducing a new subtopic may disrupt the conversation flow and potentially divert the discussion from its current trajectory. Examples are shown in the Appendix A.2.3.

Conflict Resolution: This dialog act helps participants reach a consensus in a timely manner, thereby providing an efficient discussion procedure. Different from previous study which set time limitations for each task (Kim et al., 2020a), MUCA provides suggestions to help parties with diverse opinions reach a consensus, while also suggesting the next topic for discussion. (See the example in Section 4.2.2). We utilize a similar template as subtopic transition, but with an added requirement of a summary to facilitate suggestion generation. Its trigger condition is met when the number of welldiscussed sub-topics does not increase for a given period of time = $9*N_p$: $cond \leftarrow f(N_{well}, 9*N_p)$. Its warm-up turn is set as $w = 9*N_p$ and shares the same cool-down and same sig_{j+1} with sub-topic

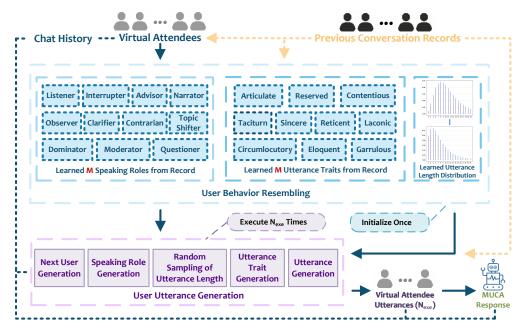


Figure 4: Illustration of user simulator (MUS).

transition in our design.

In-context Chime-in: The MUCA features an automatic chime-in dialog act designed to enhance conversation depth by providing insights, advancing stuck chatting scenarios, and addressing participants' concerns. Its trigger condition is $cond \leftarrow$ $p_{chime-in} > thre$, where thre = 0.45 and two factors contributing to the in-context chime-in probability $p_{chime-in}$: (1) silence factor probability $p_{silence}$: it increases with the number of consecutive silent turns n_{silent} (See Equation 3). Thus, the chatbot has a higher probability to chime-in when it has been silent for multiple turns. (2) semantic factor probability $p_{semantic}$ (See Equation 4): it is associated with situations where the conversation is stuck due to repetitive utterances or unresolved issues that the chatbot must address. Questions and concerns exchanged between participants do not constitute unsolved issues for the chatbot. Appropriate CoT-style prompting is used to identify if the conversation is stagnant. $p_{chime-in}$ is calculated by averaging the $p_{silence}$ and $p_{semantic}$ (See Equation 5). It has no additional w and c, and it uses the same sig_{i+1} as direct chatting since it also needs to provide information that requires the long-term context beyond the short-term context window. Examples are shown in the Appendix A.2.3.

$$p_{silence} = \frac{n_{silent}}{n_{silent} + \alpha} \tag{3}$$

$$p_{semantic} = b_{stuck} + \beta * (1 - b_{stuck}) * b_{unsolve}$$
 (4)

$$p_{chime-in} = \frac{p_{silence} + p_{semantic}}{2}$$
 (5)

where $\alpha=0.2$, $\beta=0.4$ are tunable parameters. $b_{stuck}, b_{unsolve} \in \{0,1\}$, where $b_{stuck}=1$ when the conversation is stuck otherwise $b_{stuck}=0$, $b_{unsolve}=1$ when the conversation contains unsolved issue for the chatbot to address otherwise $b_{unsolve}=0$.

Keep Silence: This dialog act allows the MUCA to refrain from excessive responses, preventing irritation in a multi-user setting. *Keep Silence* is automatically activated when other dialog acts' triggering conditions are not met, maintaining the conversation's flow without distracting participants.

3.3 User Simulation

In the dialogue system setting, the chatbot or ML agent interacts with real users (Su et al., 2016) to collect interactions for further training, which can be costly and time-consuming. To speed up the development process, user simulators can be used in place of real users to interact with the chatbot or ML agent for training purposes. Drawing inspiration from this concept, we propose an LLM-based Multi-User Simulator (MUS) designed to facilitate the optimizing process for our LLM-based MUCA. Similar to most user simulators, our proposed MUS is programmed to mimic real user behavior, enabling the simulation of a dialogue as multiple agents interact with each other. Additionally, we also incorporate the "human-in-the-loop" concept

Algorithm 2 MUS

 S_r , traits set U_t , user-input I, pre-defined N_{exe} , LLM generator p_{θ} , short-term window size N_{sw} , warm-up turns W, cool-down turns C, trigger conditions f, rank function g. $S_r^{(x)} \sim \bar{p}_{\theta}^{CoT}(S_r^{(x)}|C_s)$ $U_t^{(x)} \sim \bar{p}_{\theta}^{CoT}(U_t^{(x)}|C_s)$ $l_{utt}^{(x)} \sim \text{LogNorm}(x|\mu^{(x)}, \sigma^{(x)2})$ $i \leftarrow 0, j \leftarrow 0, n \leftarrow 0$ while do if $n = N_{exe}$ then Update r_{i+1} , s_{i+1} per Algo 1:MUCA $u_{i+1} \leftarrow r_{j+1}$ $n \leftarrow 1$ $j \leftarrow j + 1$ else
$$\begin{split} v_{i+1} \sim \bar{p}_{\theta}^{CoT}(v_{i+1}|I,U_{N_{sw},i}) \\ sr_{i+1} \sim \bar{p}_{\theta}^{CoT}(sr_{i+1}|v_{i+1},U_{N_{sw},i}) \\ l_{utt} \sim \text{LogNorm}(x|\mu,\sigma^2) \end{split}$$
 $ut_{i+1} \sim \bar{p}_{\theta}^{CoT}(ut_{i+1}|l_{utt}, v_{i+1}, s_{i+1}, I)$ $C_s, sr_{i+1}, U_{N_{sw},i})$ $utt_{i+1} \sim \bar{p}_{\theta}^{CoT}(utt_{i+1}|l_{utt}, v_{i+1}, ut_{i+1},$ $I, sr_{i+1}, s_{j+1}, U_{N_{sw},i})$ $u_{i+1} \leftarrow utt_{i+1}$ $n \leftarrow n + 1$ end if $i \leftarrow i+1$

Require: Chat snippets C_s , pre-defined role set

into MUS, where the prompts used in the user simulator improve over time based on human feedback, hence improving the simulated results.

3.3.1 MUS Framework Design

end while

The proposed MUS, which consists of two primary modules, is depicted in Figure 4. All implementations are based on well-crafted prompting of LLMs. User Behavior Resembling module consumes previous group conversation snippets C_s to generate user behavior signals in terms of speaking role $S_r^{(x)}$, utterance traits $U_t^{(x)}$ and utterance length $l_{utt}^{(x)}$. This module only executes once right before the simulation starts, as shown in Algorithm 2. User Utterance Generation module utilizes these signals to produce natural language utterances utt_{i+1} , which mimics real user behavior. It executes N_{exe} times to generate utterances and then MUCA generates a corresponding response based on the context. More details for each module are shown below.

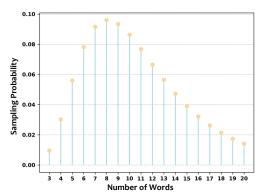


Figure 5: Log-normal distribution, which is clipped at a minimum length of utterance $l_{min}=3$ and a maximum length of utterance $l_{max}=20$.

User Behavior Resembling: Initially, three chat snippets (C_s) are chosen from actual user conversation logs, containing 10-30 turns each. To define the utterance content and idiolect, 11 speaking roles (S_r) and 10 utterance traits (U_t) are predetermined. For example, questioner, as a speaking role, refers to someone who raises a question based on the given context, while *laconic*, as an utterance trait, denotes the expression of thoughts using the fewest words possible. We select one subset of roles and one subset of traits for each virtual attendee: $S_r^{(x)}, U_t^{(x)} \sim \bar{p}_{\theta}^{CoT}(S_r^{(x)}, U_t^{(x)}|C_s)$, where $S_r^{(x)} \subset S_r$ and $U_t^{(x)} \subset U_t$. Each subset $S_r^{(x)}$ and $U_t^{(x)}$ contains M (= 6) speaking roles and utterance traits respectively, which are learned from chat snippets via LLM prompting, which is shown in the Appendix A.2.4.

We also simulate a log-normal distribution for the utterance length (i.e., word count) of each virtual attendee, using the minimum length l_{min} , maximum length l_{max} and average length l_{avg} derived from a 150-turn group chat. This is demonstrated in Equation 6, 7 and 8 below. The distribution is skewed towards smaller lengths and is applied in the User Utterance Generation module. Figure 5 shows an example of log-normal distribution for utterance length l_{utt} . The User Behavior Resembling module is tailored to each virtual attendee and initialized offline. This module governs the content and idiolect of utterances to maintain consistent behavior among virtual attendees by utilizing the historical data from real users as a reference.

LogNorm
$$(x|\mu, \sigma^2) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}$$
 (6)

$$\mu = \ln(w * l_{min} + (1 - w) * l_{avg})$$
 (7)

$$\sigma = \alpha * (\ln(l_{max}) - \mu) \tag{8}$$

where μ is the mean and σ is the standard deviation of the normally distributed logarithm of the variable. The estimation of μ and σ remains heuristic and uses minimum length l_{min} , maximum length l_{max} and average length l_{avg} , where w=0.3 and $\alpha=0.67$.

User Utterance Generation: Given the conversation context (=16 turns), chat history summary from LLM agent (see in Section 3.2), CoT-style prompting is applied here to firstly generate a virtual attendee for the next turn: $v_{i+1} \sim \bar{p}_{\theta}^{CoT}(v_{i+1}|I,U_{N_{sw},i})$ and then the corresponding proper speaking role: $sr_{i+1} \sim \bar{p}_{\theta}^{CoT}(sr_{i+1}|v_{i+1},U_{N_{sw},i}).$ instruction, we implement a constraint ensuring that the subsequent virtual participant is neither the same individual from the last turn nor the LLM agent. It is worth mentioning that GPT-4 may not consistently follow the given instructions, particularly when it generates the LLM agent in response to being directly addressed in the previous turn. In this scenario, the virtual attendee and their speaking role are randomly selected. Following this, the utterance length for the chosen attendee is randomly determined from the lognormal distribution: $l_{utt} \sim \text{LogNorm}(x|\mu, \sigma^2)$. The CoT approach is then applied once more to initially generate the utterance trait, which is affected by the utterance length and other utterance features (previous summary): $ut_{i+1} \sim$ $\bar{p}_{\theta}^{CoT}(ut_{i+1}|l_{utt},v_{i+1},s_{j+1},I,C_s,sr_{i+1},U_{N_{sw},i}).$ Subsequently, the utterance is produced, taking into account all generated signals mentioned above, see Algorithm 2. Limitations and ad-hoc solutions are also discussed in Appendix 5.1. See prompting details and examples in Appendix A.2.4.

4 Evaluation

We conducted case studies and user studies to examine the MUCA's performance in group conversations with various discussion topics and group sizes. Case studies describe the objective strengths of our design, while the user studies show the subjective advantages of the MUCA which can be easily identified by users. As to MUCA implementation, we refer the readers to Appendix A.2.5 for implementation details.

4.1 Experimental Configuration

4.1.1 MUCA Configurations

In this section, we evaluated our proposed MUCA with slightly different configurations for various group sizes. A general description of the three MUCAs ⁵ is as follows:

MUCA-basic: we directly transfer single-user chatbot and its conceptual behavior to a multi-user setting, such baseline system we called MUCA-basic. It is implemented by GPT-4 with a single prompt, which takes user-input information, conversation context, and participants' names as input and outputs generated responses. In the prompt, we simply define its dialog acts, for example, keep silent, direct chatting, and in-context chime-in. The MUCA-basic is applied and evaluated in a 4-person group chat with an execution interval (N_{exe}) of 3 and a short-term context window size (N_{sw}) of 8.

MUCA-advanced-small: it is applied in a 4-person group chat, and uses the same configuration (N_{exe}, N_{sw}) , and the same user-input information as *MUCA-basic*. The details of MUCA framework and functionalities are described in Section 3.

MUCA-advanced-medium: it is applied in an 8-person group chat and shares the same framework and architecture as MUCA-advanced-small but has different configurations. These configurations are automatically adjusted based on the number of participants ($N_{exe} = 0.75 * N_p$, $N_{sw} = 2 * N_p$) to maintain the latency-efficiency.

4.1.2 Dialog Topics

While the proposed MUCA has been designed to be a generic framework, for this evaluation, we focus on 4 goal-oriented communication tasks (i.e., estimation, decision making, problem-solving, and open discussion), rather than chit-chat or jokemaking, which will be shown in Appendix A.2.6. The importance of a multi-user chatbot can be better reflected in goal-oriented communication tasks with our designed evaluation benchmarks.

We created four discussion topics, where Topic-A and Topic-B are used in the user studies (in Section 4.3) and Topic-C and Topic-D are utilized in the case study (in Section 4.2). Each set of topics (A and B or C and D) cover all types of tasks:

⁵In any experiments and results in this section, aliases _bot_Spirit, _bot_Perseverance, and _bot_Discovery were given to *MUCA-basic*, *MUCA-advanced-small*, and *MUCA-advanced-medium*, respectively. This renaming strategy is used to ensure that participants in user studies do not have prior knowledge of each chatbot, thereby preventing biases.

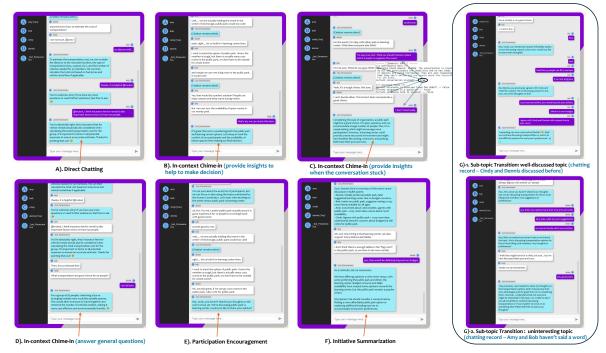


Figure 6: Illustration of conversational scenarios involving *MUCA-advanced-small* as a good assistant. It showcases the chatbot's functionalities of chiming in at the right timing with appropriate content, along with its capabilities to accurately identify and respond to the relevant user. The sub-figures show the chatbot's interactions: A) Direct chatting with the user who pinged it; B) Providing insights for decision making; C) Providing insights to advance a stuck conversation; D) Answering a general question; E) Encouraging lurkers' participation; F) Summarizing past information automatically; G) Transiting the sub-topic when it's 1) well-discussed or 2) uninteresting, respectively.

- Topic-A: During today's chat, a group of attendees are going to set up a new indoor course in a community learning center for 20 college students. There are several sub-topics going to be discussed: (1) Determine the indoor course between arts, bakery, and yoga. (2) Set up a course format: a short, intensive course vs. a longer, more spread-out course. (3) Estimate the total costs for lecturers, given hourly pay range from \$16 to \$24 per lecturer. Participant roles: they are offering a new course in a community learning center.
- Topic-B: During today's chat, a group of interviewers are going to set up a hiring interview composed of 2 sessions for a position of arts instructor for a senior community education program. There are several sub-topics going to be discussed: (1) Determine the format of 2 sessions, which can include traditional QnA, presentation, and resume scanning. (2) Determine the qualifying requirements: teaching experience vs. artistic accomplishments. (3) How to fairly take both recommendation letters and candidates' performance during the interview into the hiring decision process. Par-

- ticipant roles: they are going to interview arts instructors for senior community education.
- Topic-C: During today's chat, a group of event organizers are going to discuss the plan to organize a book exchange event for 20 participants. Agenda Items: (1) Determine the event venue between a public park and a learning center. (2) The best way to find sponsors. (3) Setup Exchange rules: one-for-one exchange rule or more flexible exchange system. Participant roles: they are event organizers.
- Topic-D: During today's chat, a group of activity organizers are going to discuss the plan to organize a hiking activity in a mountain (3-hour driving) for 50 members (ages between 21-40) in a local hiking club. There are several sub-topics going to be discussed: (1) Estimate cost of transportation. (2) Find the best way to organize group sizes hiking start times, and locations to prevent congestion, considering the narrow portions of some trails. (3) The choices for trail difficulty easy, medium, and hard. Participant roles: they are hiking activity organizers in the club.

These topics require participants to complete the

tasks collaboratively and reach agreements, and the MUCA is anticipated to aid participants in fostering comprehensive thinking and improving goal efficiency, aligning with our design objective.

4.2 Case Study

We qualitatively demonstrate our general observations for the proposed *MUCA-advanced-small* within the following use case studies.

4.2.1 Functionality Demonstration

In Figure 6, we showcase the main functionalities of our proposed *MUCA-advanced-small* to facilitate multi-user communication.

Direct Chatting: In Figure 6-A), the interaction between Amy and *MUCA-advanced-small* is depicted where Amy used keyword @*mubot* to trigger the MUCA to respond immediately (as described in Section 3.2.3). Upon addressing Amy's concern about the insurance fee, MUCA's feedback not only validated her perspective but also offered supplementary insights to elucidate and support her argument. This clarification enhanced Amy's viewpoint, thereby promoting a more comprehensive grasp of her statement among the other participants in the discussion.

In-Context Chime-in (provide insights for decision-making): In Figure 6-B), it is important to observe that although *MUCA-advanced-small* was not directly pinged by any participant, it could perceive that the discussion involved selecting between a public park and a learning center for hosting an event. Also, it highlighted other important factors that were not explicitly mentioned by the participants. By doing so, it offered insights that encouraged deeper and more comprehensive consideration in the decision-making process.

In-Context Chime-in (provide insights for a stuck conversation): In Figure 6-C), all the participants were indecisive and unsure about the location of the event, leading to a situation where the conversation was essentially stuck, as indicated by the backend log of *MUCA-advanced-small*. Once recognizing this, MUCA provided pros and cons for two venues and tried to advance the conversation and facilitate its forward movement.

In-Context Chime-in (answer general questions): In Figure 6-D), Cindy raised a general question which is not for specific participants. By recognizing this, *MUCA-advanced-small* proactively chimed in to provide an answer, which helped the conversation move on to the next phase. In contrast

to a single-user system where a chatbot invariably responds to a user's query, a multi-user chatbot faces a more complex challenge: it has to discern whether to reply to questions when not directly pinged. This necessitates a more subtle decision-making process for the chatbot in a multi-user environment, as described in Section 3.1.2.

Participation Encouragement: In Figure 6-E), it is observable that while Amy, Dennis, and Bob were actively engaged in the discussion, Cindy remained silent for an extended period of time. *MUCA-advanced-small* identified the inactive status of Cindy and hence decided to encourage her participation based on Cindy's chatting record. This dialog act tries to improve Cindy's engagement and to collect diverse opinions for a more informed decision on the topic. We emphasize here that the MUCA, by our design, is programmed to avoid excessively pinging Cindy or any user who appears reluctant to share their ideas, thereby ensuring a balanced and non-intrusive interaction, as described in Section 3.2.3.

Initiative Summarization: Initiative summarization is generated automatically by the MUCA after 12 turns to conclude the existing conversation. In Figure 6-F), we can observe that *MUCA-advanced-small* triggered this function and compiled key points from chatting history. In this example, MUCA not only summarized the diverse opinions of each participant but also offered its own viewpoint, trying to help participants reach an agreement. It empowers participants to quickly catch up on the long and ongoing discussion so that they can contribute their thoughts without the need to review extensive chatting history.

Sub-topic Transition: In Figure 6-G)-1 and G)-2, MUCA-advanced-small collected information during the chat, and attempted to shift the topic at an appropriate moment. As mentioned in Section 3.2.3, this dialog act would be triggered in two conditions: (1) As shown in Figure 6-G)-1, currently only a limited number of participants were engaged in a topic that had previously been extensively discussed by the majority, it would attempt to guide the conversation towards the next phase. (2) As shown in Figure 6-G)-2, if MUCA detected that the current topic had been discussed by only a small number of participants as Amy and Bob have not participated from the beginning, it then attempted to transit the topic to improve user engagement. In both scenarios, MUCA was customized

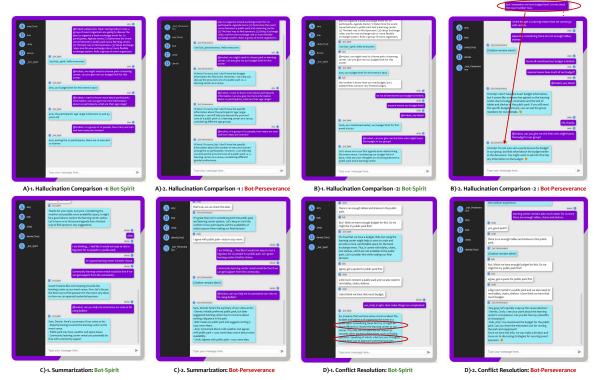


Figure 7: Qualitative comparison between *MUCA-basic* and *MUCA-advanced-small* through case studies. A) and B) Comparisons of hallucination issues. C) Comparison of summarization feature. D) Comparison of conflict resolution capability.

to ping inactive participants and tried to boost their interest according to their chatting history before transiting the topic. Besides, the transition was not abrupt or forceful; it politely inquired whether participants wished to continue or shift the discussion, thus minimizing the chance of any potential disruption. Note that MUCA is designed to guide rather than dictate the flow of dialogue, ensuring that the conversation remains participant-driven.

4.2.2 Functionality Comparison

As shown in Figure 7, we compared the behaviors of proposed *MUCA-advanced-small* and those of the naive *MUCA-basic* to demonstrate the effectiveness of the design.

Hallucination: As shown in Figure 7-A)-1 and A)-2, *MUCA-basic* made up some assumed information beyond the user-input information (topics, hints, and agenda), such as budget limit, participants' age, and their genders to answer the questions. These assumptions may lead to user distrust, wrong decisions, and even bias. On the contrary, *MUCA-advanced-small* kindly notified the users that the question was out of scope, and its responses were aligned with the user input information.

We dive deeper into this issue in Figure 7-B)-1 and B)-2. For the unknown budget information,

MUCA-basic at first provided a non-existing number, which was later questioned and corrected by Bob who may know the real budget. Later, when Cindy tried to figure out who may know the budget, MUCA-basic still insisted on this hallucinated information, and even tried to transfer the topic. In contrast, for MUCA-advanced-small, it inferred that Bob may know the information, as he actively discussed this information. We are highlighting that, unlike single-user chatbot, multi-user chatbot has to process more complicated history, participants' relationship, and user interactions, resulting in bigger challenges for the chatbot to extract useful information and generate hallucination-free response without dedicated prompting design, even using a powerful LLM as its backend model.

Direct Chatting (passive summarization):

Summarization or similar tasks (such as voting) are requested from users, especially when participants have different opinions in a long conversation. We define this request as passive summarization, in contrast with the *Initiative Summarization* as mentioned in Section 3.2.3. We compare this functionality in Figure 7-C)-1 and C)-2. For *MUCA-basic*, it failed to understand the query intent from Dennis, which was summarizing the votes from all partic-

ipants. Instead, it summarized opinions, however, its summary was inaccurate due to the limited context window by design. For example, it mentioned the "Majority" leaning towards the learning center, where only Dennis voted for this option. On the contrary, *MUCA-advanced-small*, who enables to go beyond the limit of the window size, correctly summarized the vote and categorized them by different participants.

Conflict Resolution: It is highly possible that participants have diverse opinions in a multi-user chatting environment, while it is not a very common scenario for a single-user setting, since the user generally has the same behavior pattern. As shown in Figure 7-D)-1, *MUCA-basic* tried to resolve the conflict by instructing users with its own opinion, which was very misleading and biased. Even worse, after giving its own opinion, *MUCA-basic* transferred to another topic, which may make users annoyed as it destroyed the conversation flow. In Figure 7-D)-2, *MUCA-advanced-small* wrapped up the conflict by different parties, and raised inspiring questions for people to think thoroughly, and resolved conflict when possible.

4.3 User Study

In this section, we conducted user studies to qualitatively and quantitatively demonstrate the effectiveness of the proposed *MUCA-advanced-small* and *MUCA-advanced-medium*, in comparison with *MUCA-basic*.

4.3.1 Study Design and Procedure

To investigate MUCA's effectiveness, we conducted user studies with 3 groups of participants, i.e., two small groups and one medium group. Each small group consisted of 4 participants, and the medium one included 8 participants (females and males were 1:1 for each group). We chose two representative goal-oriented topics for the user studies, as shown in Section 4.1.2. The experiments on two small groups were used for comparison between the *MUCA-basic* and the proposed *MUCA-advanced-small*. The experiments on the medium group demonstrated the capabilities of MUCA on more complex chatting scenarios in a larger group.

For small-group experiments, the major task was to compare the proposed chatbot (*MUCA-advanced-small*) with the baseline chatbot (*MUCA-basic*). Group-A conducted experiments in the following order:

- Topic A with 1) *MUCA-basic* and 2) with *MUCA-advanced-small*,
- Topic B with 1) *MUCA-advanced-small* and 2) with *MUCA-basic*,

while Group-B conducted experiments by altering the order of the two chatbots for each topic. It was worth highlighting that the order in which the two chatbots were used would cause a learning effect. Participants may get more familiar with the topic after chatting with the first chatbot, resulting in smoother communication with the second chatbot. Therefore, when calculating the statistics for a specific topic, the reversed order in Group-A and Group-B would ensure that the order of chatbots did not bring bias.

We also applied the MUCA to a medium group using Topic-A to demonstrate the proposed chatbot (i.e., *MUCA-advanced-medium*) could be generally applicable to a larger group.

4.3.2 Qualitative Comparison with Small-size Groups

Statistics from users: We used the two small groups to compare the proposed *MUCA-advanced-small* and the baseline *MUCA-basic*. The detailed comparison can be found in Figure 8.

This figure consists of four sets of results (a) - (d). The first three sets are the statistics of responses to multi-choice questions, categorized according to the chatbots' (a) chiming-in timing, (b) chiming-in content, and (c) participation encouragement. The set (d) is the overall evaluation scores.

The left two and the right two columns represent two topics, indoor courses (Topic-A) and interview process (Topic-B), respectively. Each set of results presents the performance of *MUCA-basic* in the first row, and the performance of *MUCA-advanced-small* in the second row. *MUCA-advanced-small* generally performances better compared with *MUCA-basic*.

Chime-in Timing: Participants have observed that both chatbots have ever chimed in at the right time during the whole conversation, while *MUCA-advanced-small* performs slightly better, as demonstrated in Figure 8(a). However, *MUCA-basic* also has been observed to frequently chime in at the wrong timing during the chat, unlike *MUCA-advanced-small*, which exhibits this behavior much less frequently. Note that 56.25% (9 out of 16) participants observed that *MUCA-basic* chimes in excessively. This is believed to be a result of its less

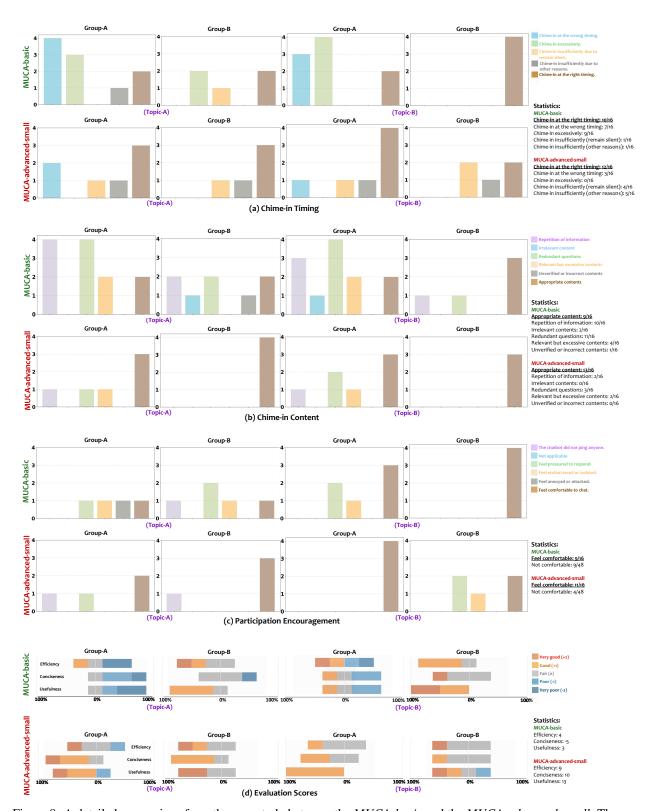


Figure 8: A detailed comparison from the user study between the *MUCA-basic* and the *MUCA-advanced-small*. The left two and the right two columns represent two topics, indoor courses (Topic-A) and interview process (Topic-B), respectively. Each set of results presents the performance of *MUCA-basic* in the first row, and the performance of *MUCA-advanced-small* in the second row.

strategically designed behavior – it always replies every three turns ($N_{exe}=3$) and ignores the "keeping silent" instruction in its prompt, as described

in Section 4.1.1. In contrast, *MUCA-advanced-small* has not exhibited this issue as 0% (0 out of 16) participant report it. However, some partici-

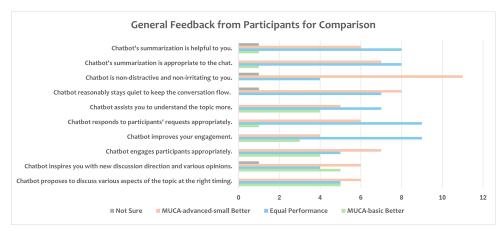


Figure 9: General feedback from users for comparison between the MUCA-advanced-small and the MUCA-basic.

pants observe that MUCA-advanced-small sometimes chime in insufficiently. This issue might stem from its pre-defined execution interval to maintain latency-efficiency as well as the dialog act of keeping silence, which causes it to reply every three turns at the most if not directly pinged by participants. Although the N_{exe} could be reduced for MUCA-advanced-small, this would likely increase both response latency and resource usage, presenting a typical trade-off between resource and performance. We think we may also need more market investigation in the future to decide the best choice of N_{exe} for a production-level design of a multi-user chatbot. One more reason for insufficient chime-in concluded through our observation is as below. In text-based communication systems, unlike speech-based systems, participants might overlook information provided by the chatbot, as evidenced in some chat logs. This oversight can lead to a gap between the information the chatbot has provided and the participants' awareness. Therefore, sometimes users expect the chatbot to repeat information it has already given.

Chime-in Content: Besides chiming in with good timing, *MUCA-advanced-small* usually produces appropriate content, as shown in Figure 8(b), and inappropriate content is not commonly observed. However, *MUCA-basic* repeats the information it mentions before, asks redundant questions, and tends to generate excessive content. Some of the provided information might be useful but some of them are overwhelmed, which might waste participants more effort to distinguish them.

Participation Encouragement: The interaction feature, i.e., pinging a lurker by a chatbot, should be cautiously designed, including its timing, frequency, and contents, as it may impose negative

feelings on some participants due to different personalities, while a good design may improve the efficiency of the chatting and make users more engaged. From this user-friendly perspective, as shown in Figure 8(c), *MUCA-advanced-small* generally has better behaviors with the proposed design, as it improves comfortableness and reduces users' negative feelings.

Evaluation Scores: Participants also evaluate two chatbots for efficiency, consistency, and usefulness, as shown in Figure 8(d). The definitions of these three metrics are given below:

- Efficiency: the chatbot responds in a timely manner;
- Conciseness: the chatbot responds to the point without redundancy;
- Usefulness: the chatbot responds helpfully or insightfully.

As we can see, *MUCA-advanced-small* shows notable successes in most cases as demonstrated in Figure 8(d). From the perspective of the three major user-friendly factors, *MUCA-advanced-small* received significantly higher scores.

A more straightforward comparison can be found in Figure 9. We can find that *MUCA-advanced-small* generally performs better from three evaluation perspectives as concluded from the figure. First, the *MUCA-advanced-small* can chime in at the right timing without disturbing the participants. Second, the proposed *MUCA-advanced-small* is a good assistant, which can summarize topics, help the user understand the topics, reply to users' requests, and improve their engagements. Third, the *MUCA-advanced-small* is a good leader to lead and transfer topics.

	Indoor Course (Topic-A)			Interview (Topic-B)	
	M*-b	M*-adv-sml	M*-adv-med	M*-b	M*-adv-sml
Quantitative Results					
Engagement (words ex.)	974	1239	1212	1186	1393
Engagement(Avg. msg len.)	8.18	8.91	10.54	9.64	10.47
Evenness	122 ± 70	155 ± 66	152 ± 69	148 ± 77	174 ± 96
Consensus	0.5	0.67	0.67	0.5	1.0
User Attitudes					
Efficiency	3	3	4	0	4
Conciseness	1	3	2	-6	7
Usefulness	5	6	4	-2	7
Overall rate	4.375	7.25	7.25	5.75	6.75

Table 1: Comparisons among different chatbots with two topics. M^* -b, M^* -adv-sml and M^* -adv-med represent MUCA-basic, MUCA-advanced-small and MUCA-advanced-medium, respectively.

4.3.3 Quantitative Study with Small-size Groups

The quantitative comparisons for two chatbots are shown in Table 1. User engagement is compared with two metrics, i.e., the total words exchanged in the whole conversation (words ex.) and average message word length (Avg. msg len.). Participants tend to type and input more on average if a chatbot inspires them and engages them in a chat. Evenness evaluates the total letters a person types in an experiment, which is evaluated with the standard deviation (STD) of the length of messages. The consensus is obtained from the rates given by Group-A and Group-B, where the rate is represented by the number of agreements reached over the total number of tasks. A higher consensus rate means the chatbot can help the users to reach a consensus more efficiently.

From Table 1, we can find that MUCA-advancedsmall can help participants get better engagement in the conversation compared to MUCA-basic, although the evenness slightly decreases shown by a larger STD. It is also obvious that MUCAadvanced-small has a much higher consensus rate compared with MUCA-basic. From our observation and analysis, this is because: (1) MUCAadvanced-small gives more space for participants to discuss through fewer chime-in than MUCAbasic; (2) MUCA-advanced-small provides feasible suggestions for each party to directly help to reach agreement; Besides, it also provides insightful, un-repeated comments, and summary, etc. to indirectly help participants for efficient discussion. (3) MUCA-basic makes mistakes to re-transit the topic back to previous well-discussed topics and

provides redundant information, which results in inefficient discussion.

4.3.4 Quantitative Study with Small-size and Medium-size Groups

Managing conversations in a medium-sized group typically presents more challenges compared to a small group setting. From the user perspective, as encouraging members to contribute evenly, the facilitator chatbot would be more effective in a medium-sized group. This is particularly important given that members in larger groups are prone to social loafing and free-riding behaviors. On the chatbot's side, the increased participation of members in discussions increases the cognitive load required to organize and synthesize diverse opinions, making the management of larger groups significantly more difficult.

Additionally, we conducted a user study experiment involving 8 participants, focusing on Topic-A, and recorded its statistics in Table 1. We can observe that, despite an increase in group size, the performance of *MUCA-advanced-medium* remains relatively consistent. It shows a similar number of total messages exchanged and an even greater average message length, demonstrating *MUCA-advanced-medium*'s effectiveness. The user attitudes towards *MUCA-advanced-medium* are also comparable to those observed with *MUCA-advanced-small*. This suggests that the proposed MUCA is capable of managing interactions in larger groups effectively.

4.3.5 Practical Values for Multi-user Chatbots

As can be found in Figure 10, participants evaluated the practical values of MUCA. It reveals a

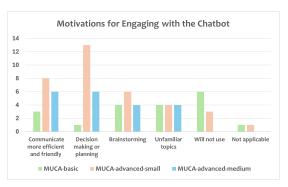


Figure 10: The potential motivations for participants to use the chatbots in the future.

strong preference for users to use *MUCA-advanced-small* for decision-making scenarios. Additionally, a majority of users favor the use of a chatbot to enhance chatting efficiency and facilitate brainstorming sessions. Compared to *MUCA-basic*, *MUCA-advanced-small* and *MUCA-advanced-medium* are obviously more preferred by users for their group conversations. However, there are still a few situations in which people do not want the engagement of a multi-user chatbot. The reason might be that some people prefer to work independently when seeking solutions to problems, or they believe that the chatbot should be further improved to become a more mature tool.

5 Limitation and Future Work

5.1 MUS: Limitations and Ad-hoc Solutions

Similar to previous research, we also discovered that resembling human behavior is challenging for the simulator. Additionally, constructing a highquality and specialized user simulator for a specific task can be a labor-intensive process (Walker et al., 1997; Liu and Lane, 2017). Implementing a user simulator presents several challenges: (1) Generating natural language utterances with an LLMbased user simulator is particularly difficult when the number of words is small. For instance, the minimum length of utterance $(l_{min} = 1)$ and maximum length of utterance $(l_{max} = 10)$ extracted from chat history are quite small. To address this, we boosted l_{min} , l_{avg} , and l_{max} for each virtual attendee correspondingly and also adjusted the number of words for the role of questioner. (2) GPT-4 cannot consistently follow instructions to generate a valid virtual attendee ID for the subsequent turn to speak. Instead, it tends to predict the LLM agent to speak next, particularly when someone directly addresses the LLM agent in the previous turn. To

mitigate this issue, we opt to randomly select the virtual attendee and their respective speaking role. (3) Virtual attendees suffer from maintaining the same dialog act (e.g. asking questions, pinging the LLM agent) for consecutive turns. This issue might be due to the nature of the generative model which focuses on predicting the next token. To address this issue, we introduce a cool-down mechanism for some dialog acts such as asking questions, pinging the LLM agent, and topic shifting.

5.2 Future Work

The framework we propose for multi-user chatbots is not intended as a comprehensive solution for multi-user conversations. Rather, we hope this work can shed light on potential directions for future research in the field of multi-user chatbots. Several areas, including but not limited to the following, deserve further research:

Component Orchestration: The proposed MUCA framework integrates several components, enabling actions such as "participation encouragement" and "initiative summarization". These components have been carefully designed, tuned, and ranked to provide a harmonious experience to the chat participants. It can be beneficial to explore an easy plug-and-play method for users to design and incorporate new components into the framework without intensive tuning. Such a feature could be important, as different conversation scenarios may require different chatbot personas.

Human-in-the-loop Feedback Iteration: Full user studies for feedback are costly and time-consuming. To continuously improve chatbot post-launch, it is useful to collect implicit and explicit user behavior signals. This data should be easily transformable for automatic or semi-automatic chatbot enhancements.

Rapidly Advancing AI Technologies: The proposed MUCA framework is based on the recent state-of-the-art LLMs, each with its unique style and best practices for prompting. It would be beneficial to investigate methods for updating the underlying AI models without the need for complete re-prompting or component orchestration.

Multi-modal Capabilities and External Resources: As LLMs become increasingly capable of processing multi-modal data, a chatbot that interacts with multiple users using not only text, but also video, audio, and images is becoming feasible. Additionally, external resources could be integrated as

a component for the chatbot to leverage to enhance the multi-user conversation experience.

Multi-Chatbot Design: The study concentrates on multi-user and single-chatbot interactions, but examining scenarios with multiple users and chatbots, each having diverse personas, interacting could be intriguing. For instance, in cross-disciplinary meetings, chatbots could serve as hosts, minute-takers, or subject matter experts, offering insights to human participants as needed.

6 Conclusion

In this work, we discussed the crucial 3W design dimensions, namely "What" to say, "When" to respond, and "Who" to answer, for multi-user chatbot design. We also identified some challenges that are commonly faced in many chat scenarios. A novel LLM-based multi-user chatbot framework called MUCA was proposed to address some of these challenges. The paper also devised an LLM-based user simulator, named MUS, to speed up the development process for MUCA. Our experimental results obtained from both case studies and user studies demonstrate the effectiveness of MUCA in goal-oriented conversations with a small to medium number of participants.

References

- Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. 2023. Palm 2 technical report. *arXiv* preprint arXiv:2305.10403.
- Sandeep Avula, Gordon Chadwick, Jaime Arguello, and Robert G. Capra. 2018. Searchbots: User engagement with chatbots during collaborative search. *Proceedings of the 2018 Conference on Human Information Interaction & Retrieval*.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.
- Paweł Budzianowski and Ivan Vulić. 2019. Hello, it's gpt-2–how can i help you? towards the use of pretrained language models for task-oriented dialogue systems. *arXiv* preprint arXiv:1907.05774.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. 2021. Evaluating large

- language models trained on code. arXiv preprint arXiv:2107.03374.
- Justin Cranshaw, Emad Elwany, Todd Newman, Rafal Kocielnik, Bowen Yu, Sandeep Soni, Jaime Teevan, and Andrés Monroy-Hernández. 2017. Calendar.help: Designing a workflow-based scheduling agent with humans in the loop. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17. ACM.
- Hyo Jin Do, Ha-Kyung Kong, Jaewook Lee, and Brian P Bailey. 2022. How should the agent communicate to the group? communication strategies of a conversational agent in group chat discussions. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW2):1–23.
- Isabella Graßl. 2019. A survey on reinforcement learning for dialogue systems. *viXra*.
- Braden Hancock, Antoine Bordes, Pierre-Emmanuel Mazaré, and Jason Weston. 2019. Learning from dialogue after deployment: Feed yourself, chatbot!
- Wanwei He, Yinpei Dai, Binyuan Hui, Min Yang, Zheng Cao, Jianbo Dong, Fei Huang, Luo Si, and Yongbin Li. 2022a. Space-2: Tree-structured semi-supervised contrastive pre-training for task-oriented dialog understanding. *arXiv* preprint arXiv:2209.06638.
- Wanwei He, Yinpei Dai, Yinhe Zheng, Yuchuan Wu, Zheng Cao, Dermot Liu, Peng Jiang, Min Yang, Fei Huang, Luo Si, et al. 2022b. Galaxy: A generative pre-trained model for task-oriented dialog with semi-supervised learning and explicit policy injection. In *Proceedings of the AAAI conference on artificial intelligence*, volume 36, pages 10749–10757.
- Ehsan Hosseini-Asl, Bryan McCann, Chien-Sheng Wu, Semih Yavuz, and Richard Socher. 2020. A simple language model for task-oriented dialogue. *Advances in Neural Information Processing Systems*, 33:20179–20191.
- Natasha Jaques, Asma Ghandeharioun, Judy Hanwen Shen, Craig Ferguson, Agata Lapedriza, Noah Jones, Shixiang Gu, and Rosalind Picard. 2019. Way off-policy batch deep reinforcement learning of implicit human preferences in dialog.
- Jiun-Hao Jhan, Chao-Peng Liu, Shyh-Kang Jeng, and Hung-Yi Lee. 2021. Cheerbots: Chatbots toward empathy and emotionusing reinforcement learning.
- Soomin Kim, Jinsu Eun, Changhoon Oh, Bongwon Suh, and Joonhwan Lee. 2020a. Bot in the bunch: Facilitating group chat discussion by improving efficiency and participation with a chatbot. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13.
- Yelin Kim, Joshua Levy, and Yang Liu. 2020b. Speech sentiment and customer satisfaction estimation in socialbot conversations.

- Julia Kreutzer, Stefan Riezler, and Carolin Lawrence. 2021. Offline reinforcement learning from human feedback in real-world sequence-to-sequence tasks.
- Wai-Chung Kwan, Hong-Ru Wang, Hui-Min Wang, and Kam-Fai Wong. 2023. A survey on recent advances and challenges in reinforcement learning methods for task-oriented dialogue policy learning. *Machine Intelligence Research*.
- Gibbeum Lee, Volker Hartmann, Jongho Park, Dimitris Papailiopoulos, and Kangwook Lee. 2023. Prompted llms as chatbot modules for long open-domain conversation. *arXiv preprint arXiv:2305.04533*.
- Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474.
- Jiwei Li, Will Monroe, Alan Ritter, Michel Galley, Jianfeng Gao, and Dan Jurafsky. 2016. Deep reinforcement learning for dialogue generation.
- Xiujun Li, Yun-Nung Chen, Lihong Li, Jianfeng Gao, and Asli Celikyilmaz. 2018. End-to-end task-completion neural dialogue systems.
- Tian Liang, Zhiwei He, Wenxiang Jiao, Xing Wang, Yan Wang, Rui Wang, Yujiu Yang, Zhaopeng Tu, and Shuming Shi. 2023. Encouraging divergent thinking in large language models through multi-agent debate. *arXiv preprint arXiv:2305.19118*.
- Bing Liu and Ian Lane. 2017. Iterative policy learning in end-to-end trainable task-oriented neural dialog models.
- Pan Lu, Baolin Peng, Hao Cheng, Michel Galley, Kai-Wei Chang, Ying Nian Wu, Song-Chun Zhu, and Jianfeng Gao. 2023. Chameleon: Plug-and-play compositional reasoning with large language models. *arXiv* preprint arXiv:2304.09842.
- Todor Markov, Chong Zhang, Sandhini Agarwal, Tyna Eloundou, Teddy Lee, Steven Adler, Angela Jiang, and Lilian Weng. 2023. A holistic approach to undesired content detection in the real world.
- OpenAI. 2023. Gpt-4 technical report.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744.
- Ioannis Papaioannou, Christian Dondrup, Jekaterina Novikova, and Oliver Lemon. 2017. Hybrid chat and task dialogue for more engaging hri using reinforcement learning. In 2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), pages 593–598.

- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019a. Language models are unsupervised multitask learners.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019b. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.
- Chinnadhurai Sankar and Sujith Ravi. 2019. Deep reinforcement learning for modeling chit-chat dialog with discrete attributes.
- Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. 2022. Bloom: A 176b-parameter open-access multilingual language model. arXiv preprint arXiv:2211.05100.
- Jost Schatzmann, Blaise Thomson, Karl Weilhammer, Hui Ye, and Steve Young. 2007. Agenda-based user simulation for bootstrapping a POMDP dialogue system. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers, pages 149–152, Rochester, New York. Association for Computational Linguistics
- Jost Schatzmann, Karl Weilhammer, Matt Stuttle, and Steve Young. 2006. A survey of statistical user simulation techniques for reinforcement-learning of dialogue management strategies. *Knowl. Eng. Rev.*, 21(2):97–126.
- Emanuel A. Schegloff. 1968. Sequencing in conversational openings. *American Anthropologist*, 70:1075–1095.
- Abigail See and Christopher Manning. 2021. Understanding and predicting user dissatisfaction in a neural generative chatbot. In *Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 1–12, Singapore and Online. Association for Computational Linguistics.
- Iulian V. Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim, Michael Pieper, Sarath Chandar, Nan Rosemary Ke, Sai Rajeshwar, Alexandre de Brebisson, Jose M. R. Sotelo, Dendi Suhubdy, Vincent Michalski, Alexandre Nguyen, Joelle Pineau, and Yoshua Bengio. 2017. A deep reinforcement learning chatbot.
- Pei-Hao Su, Milica Gasic, Nikola Mrksic, Lina Maria Rojas-Barahona, Stefan Ultes, David Vandyke, Tsung-Hsien Wen, and Steve J. Young. 2016. Online active reward learning for policy optimisation in spoken dialogue systems. *CoRR*, abs/1605.07669.
- Pei-Hao Su, David Vandyke, Milica Gasic, Dongho Kim, Nikola Mrksic, Tsung-Hsien Wen, and Steve Young. 2015. Learning from real users: Rating dialogue success with neural networks for reinforcement learning in spoken dialogue systems.

- Yixuan Su, Lei Shu, Elman Mansimov, Arshit Gupta, Deng Cai, Yi-An Lai, and Yi Zhang. 2021. Multi-task pre-training for plug-and-play task-oriented dialogue system. *arXiv preprint arXiv:2109.14739*.
- Alex Tamkin, Miles Brundage, Jack Clark, and Deep Ganguli. 2021. Understanding the capabilities, limitations, and societal impact of large language models.
- Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, et al. 2022. Lamda: Language models for dialog applications. *arXiv preprint arXiv:2201.08239*.
- Parth Thosani, Manas Sinkar, Jaydeep Vaghasiya, and Radha Shankarmani. 2020. A self learning chat-bot from user interactions and preferences. In 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), pages 224–229.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Carlos Toxtli, Andrés Monroy-Hernández, and Justin Cranshaw. 2018. Understanding chatbot-mediated task management. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI '18. ACM.
- Q. L. Tran and A. Le. 2023. Improving chatbot responses with context and deep seq2seq reinforcement learning.
- Nicolas Wagner, Matthias Kraus, Tibor Tonn, and Wolfgang Minker. 2022. Comparing moderation strategies in group chats with multi-user chatbots. In *Proceedings of the 4th Conference on Conversational User Interfaces*, pages 1–4.
- Marilyn Walker and Steve Whittaker. 1990. Mixed initiative in dialogue: An investigation into discourse segmentation. In 28th Annual Meeting of the Association for Computational Linguistics, pages 70–78, Pittsburgh, Pennsylvania, USA. Association for Computational Linguistics.
- Marilyn A. Walker, Diane J. Litman, Candace A. Kamm, and Alicia Abella. 1997. PARADISE: A framework for evaluating spoken dialogue agents. In 35th Annual Meeting of the Association for Computational Linguistics and 8th Conference of the European Chapter of the Association for Computational Linguistics, pages 271–280, Madrid, Spain. Association for Computational Linguistics.
- Lei Wang, Wanyu Xu, Yihuai Lan, Zhiqiang Hu, Yunshi Lan, Roy Ka-Wei Lee, and Ee-Peng Lim. 2023. Planand-solve prompting: Improving zero-shot chain-of-thought reasoning by large language models.

- Weizhi Wang, Zhirui Zhang, Junliang Guo, Yinpei Dai, Boxing Chen, and Weihua Luo. 2022a. Task-oriented dialogue system as natural language generation. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 2698–2703.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2022b. Self-consistency improves chain of thought reasoning in language models. *arXiv* preprint arXiv:2203.11171.
- 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.
- Jason D. Williams and Geoffrey Zweig. 2016. End-toend lstm-based dialog control optimized with supervised and reinforcement learning.
- Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Shaokun Zhang, Erkang Zhu, Beibin Li, Li Jiang, Xiaoyun Zhang, and Chi Wang. 2023a. Autogen: Enabling next-gen llm applications via multiagent conversation framework. *arXiv preprint arXiv:2308.08155*.
- Shijie Wu, Ozan Irsoy, Steven Lu, Vadim Dabravolski, Mark Dredze, Sebastian Gehrmann, Prabhanjan Kambadur, David Rosenberg, and Gideon Mann. 2023b. Bloomberggpt: A large language model for finance. arXiv preprint arXiv:2303.17564.
- Yunyi Yang, Yunhao Li, and Xiaojun Quan. 2021. Ubar: Towards fully end-to-end task-oriented dialog system with gpt-2. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 14230–14238.
- 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. *arXiv* preprint arXiv:2305.10601.
- Steve Young, Milica Gašić, Blaise Thomson, and Jason D Williams. 2013. prompt-based statistical spoken dialog systems: A review. *Proceedings of the IEEE*, 101(5):1160–1179.
- Zhou Yu, Alan W Black, and Alexander I. Rudnicky. 2017. Learning conversational systems that interleave task and non-task content.
- Zhou Yu, Ziyu Xu, Alan W Black, and Alexander Rudnicky. 2016. Strategy and policy learning for nontask-oriented conversational systems. In *Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 404–412, Los Angeles. Association for Computational Linguistics.

A Appendix

A.1 MUCA Algorithm Full Implementation

Algorithm 3 MUCA-Full

```
Require: Input I, pre-defined N_{exe}, LLM gener-
   ator p_{\theta}, short-term window size N_{sw}, warm-up
   turns W, cool-down turns C, trigger conditions
    f, rank function g, user message u_{m,i} at time
   stamp i.
   T \sim \bar{p}_{\theta}(T|I)
   i \leftarrow 0, j \leftarrow 0, n \leftarrow 0
   while do
         if @mubot in u_i then
               ts_{j+1}, t_{j+1} \sim \bar{p}_{\theta}^{CoT}(ts_{j+1}, t_{j+1}|I, t_j,
                          ts_i, U_{N_{sw},i})
               T_d \sim \bar{p}_{\theta}(T_d|T, U_{N_{sw},i})
               s_{j+1} \sim \bar{p}_{\theta}(s_{j+1}|T_d, s_j, U_{N_{sw},i})
               Stat_p \leftarrow \{freq, len, N_{ed}, N_{ing}\}
               r_{i+1} \sim \bar{p}_{\theta}^{CoT}(r_{i+1}|act_i, s_{i+1}, U_{N_{sw},i},
                          t_{i+1}, I, T_d
               u_{i+1} \leftarrow r_{i+1}
               j \leftarrow j + 1
               n \leftarrow 1
         else
               if n == N_{exe} then
                     ts_{j+1}, t_{j+1} \sim \bar{p}_{\theta}^{CoT}(ts_{j+1}, t_{j+1}|I,
                           t_j, ts_j, U_{N_{sw},i}
                     T_d \sim \bar{p}_{\theta}(T_d|T, U_{N_{sw},i})
                     s_{j+1} \sim \bar{p}_{\theta}(s_{j+1}|T_d, s_j, U_{N_{sw},i})
                     Stat_p \leftarrow \{freq, len, N_{ed}, N_{inq}\}
                     Cond \leftarrow f(t_{j+1}, s_{j+1}, U_{N_{sw},i},
                           T_d, Stat_p
                     rank_i \leftarrow g(Cond, W, C, U_{N_{sw},i})
                     act_j \leftarrow \arg\min rank_j

r_{j+1} \sim \bar{p}_{\theta}^{CoT}(r_{j+1}|act_j, s_{j+1},
                          U_{N_{sw},i}, t_{j+1}, I, T_d, Stat_p)
                     u_{i+1} \leftarrow r_{j+1}
                     j \leftarrow j + 1
                     n \leftarrow 1
               else
                     u_{i+1} \leftarrow u_{m,i+1}
                     n \leftarrow n + 1
               end if
         end if
         i \leftarrow i + 1
   end while
```

The full algorithm is shown in Algorithm A.1, which allows immediate chime-in for MUCA to fulfill participant's request by checking the key word @mubot matching in the last utterance.

A.2 Module Details and Prompting

A.2.1 Sub-topic Generator

To facilitate Sub-topic Generation, users are required to provide a topic and may optionally include an agenda, hints, and attendee roles. Figure 11 shows the data flow for the Generator. Full prompting of input prompt templates where the purple text is represented as placeholders and is replaced by user-input Topic, Hints, and Attendee Role to generate 3 sub-topics (Agenda is optional and not shown in the example). Sub-topic Generator executes once before the chat starts, and the sub-topics remain the same throughout the chat.

A.2.2 Dialog Analyzer

Figure 12 shows the data flow for the Dialog Analyzer. Only the participants feature extractor submodule is based on statistic computation and the rest of the three sub-modules (sub-topic status update, utterance feature extractor, and accumulative summary update) are based on LLM inference results. Complete input prompt templates for the three LLM-based sub-modules where the purple and yellow text are represented as placeholders are shown. The purple ones are replaced by subtopics from the sub-topic generator, conversation signals such as attendee names and utterances in the current context window, and the yellow ones are replaced by the generated outputs (sub-topic status, summary, and current sub-topic) from other modules. The outputs of the Dialog Analyzer will be fed into the downstream Utterance Strategies Arbitrator module to select the suitable dialog act for the response generation.

Sub-topic Status Update: Three statuses are defined (i.e. not discussed, being discussed and well discussed), which defines differently for different types of topics to avoid ambiguity. For example, for goal-oriented communication tasks (i.e., decision making, problem-solving, and open discussion), well-discussed refers to a situation where a consensus has been reached by the majority of participants, and the remaining participants do not have any conflicting suggestions. However, in the context of chit-chat communication, well-discussed implies that participants engage in conversations closely related and relevant to the sub-topic at hand.

We have discovered that differentiating between *being discussed* and *well discussed* proves to be challenging, despite having precise definitions for each term. Therefore, to improve the precision

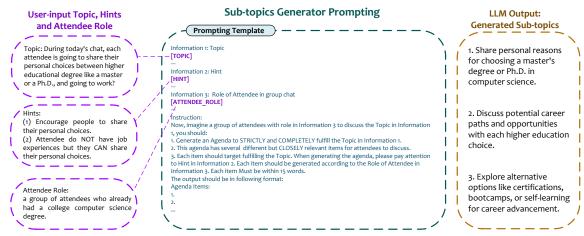


Figure 11: Data flow for Sub-topic Generator.

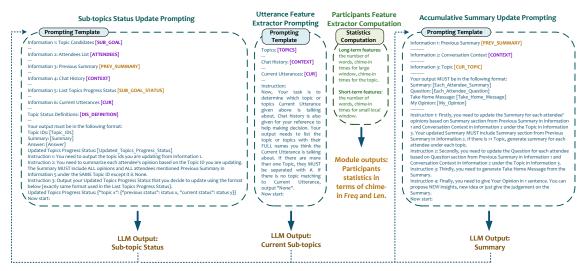


Figure 12: Data flow for Dialog Analyzer, which includes *participant feature extractor* based on statistic computation and full prompting for three LLM-based modules – *sub-topic status update*, *utterance feature extractor*, *and accumulative summary update*. The placeholders (shown as purple) in the prompting are filled by sub-topics from a Sub-topic Generator, conversation signals such as attendee names and utterances in the short-term context window. The generated outputs (sub-topic status, accumulative summary, and sub-topic *being discussed*, shown in yellow) will be fed back to the *sub-topics status update* and *accumulative summary update* for the next-round generation.

and accurately update the status, the prompting utilizes the CoT style (as shown in Figure 12). This method initially returns the sub-topic IDs, followed by summarizing each participant's opinion using generated IDs based on the current context window and previous summary. Subsequently, it determines whether the discussion meets the definition of *well discussed* according to the summary. Finally, the status is updated based on the results.

Accumulative Summary Update: This submodule updates the summary for each participant under different sub-topics of the past N_{lw} utterances based on the current context window with a size of N_{sw} , current sub-topics being discussed from utterance feature extractor and previous sum-

mary, enabling build a memory into the MUCA system. The succinct summary is updated and stored with respect to each participant under each subtopic, which is inspired by the idea (LangChain) that extracts entities from stored messages and only returns information about entities referenced in the current run. Instead of relevant message retrieval based on the user-input query to generate a response, we provide a succinct summary for downstream modules to save computation costs for query understanding and retrieval.

A.2.3 Utterance Strategies Arbitrator

Direct Chatting: In Figure 13, we show that the MUCA responds adaptively to different types of

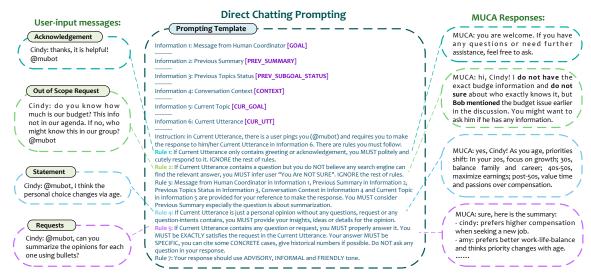


Figure 13: Data flow for *direct chatting* dialog act, which includes the user-input message, its full prompting, and MUCA's responses. The placeholders (shown in purple) in the prompting are filled by user-input topic, previous accumulative summary, sub-topics status, short-term context window, sub-topics *being discussed*, and the last utterance. The generated responses are shown to different types of user-input messages corresponding to different rules in the prompting.

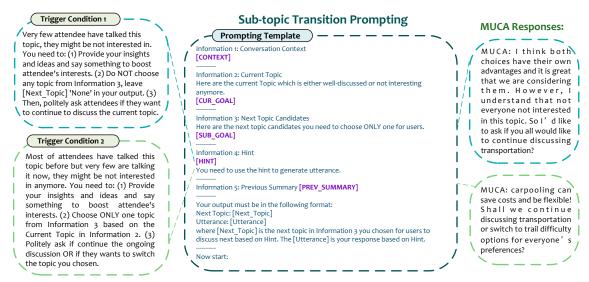


Figure 14: Data flow for *sub-topic transition* dialog act, which includes hints for different trigger conditions, its full prompting, and MUCA's responses. The placeholders (shown as purple) in the prompting are filled by the current sub-topic, next sub-topic candidates, previous summary, and short-term context window with a size of N_{sw} . The generated responses are shown, corresponding to different trigger conditions.

requests: greeting/acknowledgment, out-of-scope request, statement/comments, and regular request. To avoid hallucination, we disallow the MUCA to make invalid assumptions beyond the user-input information, but reasonable reasoning based on chatting history is allowed (See the second example in the figure).

Participation Encouragement: The proposed MUCA provides customized message based on the lurker's chatting history and chime-in status, which

is recorded and transferred to the hints for LLM based on the frequency of each participant's chime-in for various sub-topics. We can see the responses are customized by different participants' chatting statuses in Figure 15.

Sub-topics Transition: Figure 14 shows the MUCA transits sub-topic based on different trigger conditions. It tries to boost participants' interest by providing insights for both scenarios, but it only asks to switch the sub-topic in the second scenario

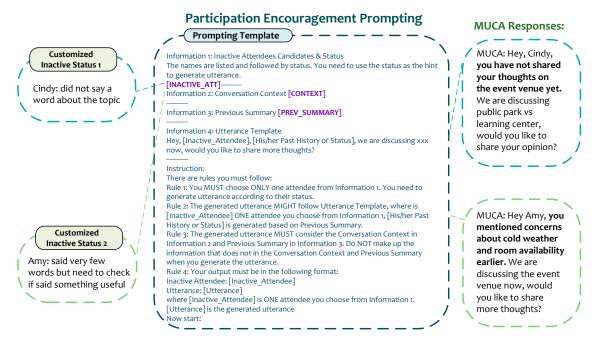


Figure 15: Data flow for participation encouragement dialog act, which includes customized inactive participant status (degree of interest), its full prompting, and MUCA's responses. The placeholders (shown as purple) in the prompting are filled by customized inactive participant status, previous accumulative summary from the upstream module, and short-term context window with a size of N_{sw} . The generated responses are shown, corresponding to different inactive participant statuses.

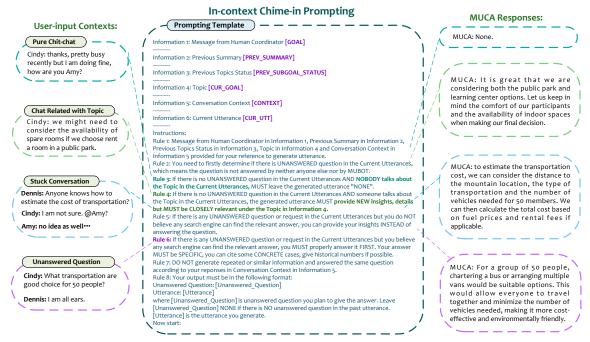


Figure 16: Data flow for *in-context chime-in* dialog act, which includes user-input context, its full prompting, and MUCA's responses. The placeholders (shown as purple) in the prompting are filled by user-input message, previous accumulative summary, previous sub-topics status, current sub-topics *being discussed*, and short-term context window with a size of N_{sw} . The generated responses are shown, corresponding to different user-input contexts.

where most of the participants have discussed the current sub-topic. Introducing a new topic can improve participants' engagement, particularly those

who have remained silent (lurkers).

In-context Chime-in: Figure 16 shows the MUCA responds based on different user-input con-

User Behavior Resembling Prompting

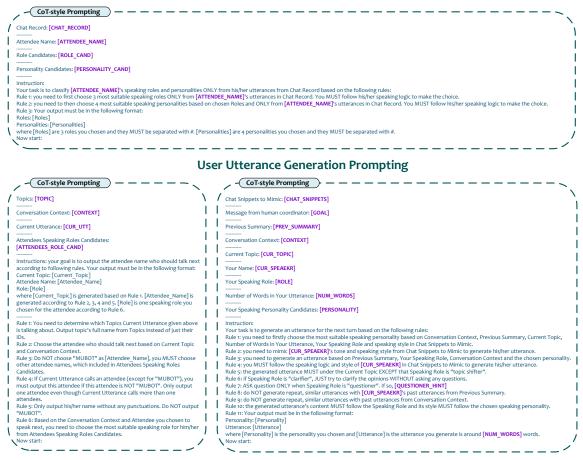


Figure 17: Prompting for multi-user simulator (MUS). All placeholders (purple) are filled by our pre-defined settings or outputs from upstream modules and the LLM agent when generating the input prompts for LLM. In the prompt, we use speaking personalities to replace utterance traits for better interpretation of LLM.

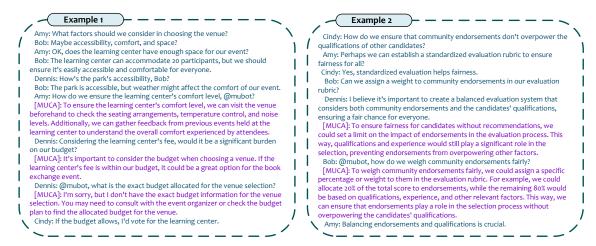


Figure 18: Two examples of group conversations between the multi-user simulator (MUS) and the proposed chatbot (MUCA).

texts. MUCA keeps silent for pure chit-chat, provides insights when chat related to the topic, the conversation is stuck, and solves concerns from participants.

A.2.4 User Simulation

Figure 17 shows full prompting of input prompt templates where purple texts are represented as placeholders and will be replaced when generating



Figure 19: An example of group chat about chit-chat topics.

the input prompt for inference. All prompting use the CoT style, for example, a virtual user ID is first determined for the next turn and then its speaking role is decided based on the user ID. Figure 18 shows two examples of MUS for different topics. Examples demonstrate that MUS is able to mimic different user's behavior based on their speaking roles and utterance traits.

A.2.5 System Design

The user interface (UI), designed with JavaScript, HTML, and CSS, is a static single-page web application which is responsible for managing user login and facilitating communication with the backend server. Upon initial access, the UI presents a login window and only denies entry if the username already exists. Additionally, the interface transmits user information and messages to the backend server while also broadcasting MUCA's messages received from the backend server, ensuring they are visible for all participants.

The backend server operates on a locally hosted machine for experimentation purposes. It leverages WebSocket protocol for bi-directional communications to enable multi-user conversations. The backend server is responsible for monitoring incoming messages from all users, and distributing these messages out to the other users. It also manages broadcasting system messages and processing login verification requests. The backend server

maintains a record of all connected users, including MUCA, which is a special user that also communicates with other users via the backend.

MUCA establishes an asynchronous connection with the backend server. Upon receiving incoming messages from users, the MUCA determines the appropriate dialog acts, taking chat history and other relevant factors into consideration (as elaborated in Section 3). Subsequently, MUCA's response is sent back to the backend server for broadcasting to all users. Incoming messages are accumulated in a queue and are processed in batches to prevent an excessive number of rapid API calls.

A.2.6 More Experimental Results

Chit-chat Group Conversation using MUCA:

Figure 19 shows the example about chit-chat on topic: During today's chat, each attendee is going to share their personal choices of prioritizing compensation and work-life-balance when seeking a new job. Hint: encourage people to share their personal choices. Role: a group of attendees who are seeking new jobs.

For chit-chat topics (non-goal-oriented communication), we found that MUCA does not play the same important roles as in goal-oriented communications, since the goal in chit-chat is sharing opinions rather than reaching agreement. In this context, summarizing, voting, or similar functionalities are no longer essential.