

WHAT, WHEN, and HOW to Ground: Designing User Persona-Aware Conversational Agents for Engaging Dialogue

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Abstract

This paper presents a method for building a personalized open-domain dialogue system to address the WWH (WHAT, WHEN, and HOW) problem for natural response generation in a commercial setting, where personalized dialogue responses are heavily interleaved with casual response turns. The proposed approach involves weighted dataset blending, negative persona information augmentation methods, and the design of personalized conversation datasets to address the challenges of WWH in personalized, open-domain dialogue systems. Our work effectively balances dialogue fluency and tendency to ground, while also introducing a response-type label to improve the controllability and explainability of the grounded responses. The combination of these methods leads to more fluent conversations, as evidenced by subjective human evaluations as well as objective evaluations.

1 Introduction

A personalized dialogue (PD) system is capable of generating user-customized responses based on long-term memory about the user's persona, leading to more trustworthy and engaging conversations (Ranjartabar et al., 2021; Xu et al., 2022). In our study, persona attributes cover comprehensive user-related information, such as personality, behaviors, preferences, and experience.

The key to enhanced user engagement in a PD system lies in finding a persona that is contextually relevant and appropriate, on which a model is grounded to generate a natural response. However, as shown in the example in Figure 1, PD systems usually need to select relevant persona attributes from a given subset of N persona attributes, which is usually provided by external memory or retrieved from the user persona pool. Considering the fact that the agent's response is usually annotated with associated oracle persona information

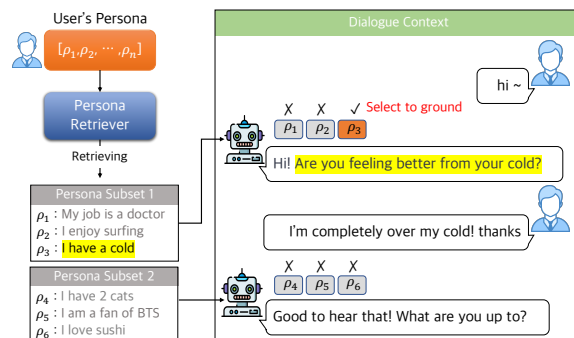


Figure 1: A sample of personalized conversation grounded on user persona. For every agent utterance, the persona attributes to be grounded in the response are retrieved by a retrieval model. Then, the agent make a decision about generating personalized response given dialogue context and retrieved persona subset.

in the training dataset, deciding what persona attribute to select in each turn during model inference is a non-trivial problem. (We will refer to this problem as the "WHAT to ground" problem hereafter.) Another aspect to consider in a PD system is that under certain dialogue contexts, it is better not to generate a personalized response given retrieved persona attributes in order to create a more natural interaction (the second response in Figure 1). As shown in the example, it is usually difficult for the retrieval module to determine whether to use persona information for response generation. We also need a model to decide when to ground persona information with a given persona subset for every turn (We will call this the "WHEN to ground" problem hereafter).

Given such a challenge, designing a user-based persona-aware PD system capable of generating engaging and human-like personalized responses requires addressing the "WHAT," "WHEN," and "HOW" (WWH) questions: 1) What personal information should be grounded given the conversation context, 2) When to generate responses using personal information, and 3) How to make natural and human-like personalized response.

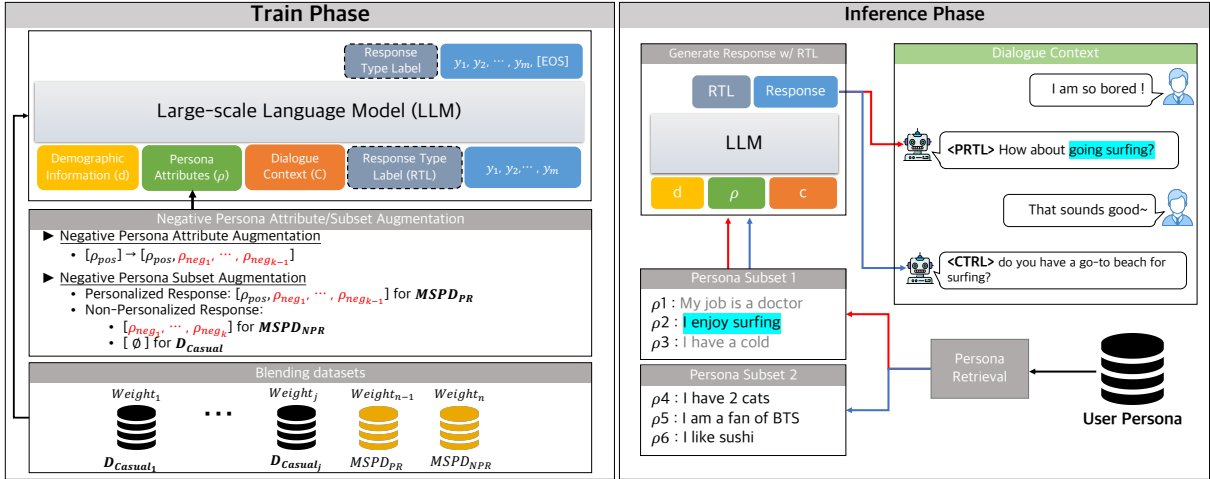


Figure 2: The overall framework of our proposed personalized dialogue system

Most previous research on personalized dialogue systems has focused on generating natural responses in ideal personalized conversation settings (Liu et al., 2020; Dong et al., 2022; Xu et al., 2022; Fu et al., 2022), where issues related to heavily interleaving personalized responses with casual dialogue turns are not considered. However, we believe that these are significant problems that need to be addressed in real-world personalized conversational systems.

Large-scale Language Models (LLMs) such as GPT-3 have shown outstanding capabilities in various Natural Language Understanding (NLU) tasks and especially, in-context learning (Brown et al., 2020). However, the inherent abilities of LLMs alone are insufficient to effectively address the WWH problems in real-world service environments. Moreover, it is very tricky to generate natural and engaging personalized responses and sophisticatedly control the output of the model in multi-turn/session scenarios, relying solely on prompt engineering.

In addressing the research gap and real-world challenges, we propose a method that controls the inclination of models to generate personalized responses. Our technique blends persona-augmented datasets to construct a personalized dialogue system, thus enabling human-like natural conversations. Our approach involves the following steps:

1) We create a Multi-Session Personalized Conversation (MSPC) dataset. This trains the model to ground the provided persona information effectively for a personalized response. 2) We control the model’s persona-grounding level by adjusting the blending weights of the conversational datasets. Furthermore, we enrich the dataset with negative

samples of persona subsets at the turn level for model fine-tuning. 3) To enhance both generation quality and the controllability and interpretability of persona-grounded generation, we use a turn label. This label indicates whether a turn is personalized or casual and serves as one of the inputs. Ultimately, we build a personalized dialogue system by fine-tuning an 18-billion parameter large language model (LLM). This LLM has a high level of understanding of conversation history, the ability to generate high-quality responses, and the capacity to focus effectively on given inputs, including users’ personas.

We also propose four grounding type categorizations to allow for analysis of the model’s grounding patterns and detailed performance in subjective evaluation using *sensibleness* and *specificity*, which complements the objective evaluation based on *groundedness*, and *fluency*.

2 Related Work

Since the release of the **PersonaChat** dataset (Zhang et al., 2018), methods to generate personalized responses that are consistent with or grounded on a persona have been extensively studied (Lee et al., 2021; Liu et al., 2020; Xu et al., 2021, 2022). Most of the studies focus on addressing the *WHAT* and *HOW* challenges by the use of diverse model architectures, modules, and training frameworks (Fu et al., 2022; Dong et al., 2022).

With respect to the *How*, Liu et al. (2020) propose an RL-based approach for generating personalized dialogue with rewards for mutual persona perception. Wu et al. (2019) and Fu et al. (2022) employ variational methods to generate personalized and knowledgeable response generation. Song

Conversation (Episode - 4 Sessions)

Session 1	
U:	오늘따라 예약이 많네... (There are so many reservations today...)
A:	예약이라면 네일아트 예약을 말하는 거야? [p4] (You mean nail art reservations?)
U:	응 너무 바빠서 밥 먹을 시간이 없을 것 같아 ㅠ (Yeah, I'm too busy to have lunch :.)
A:	그럼 점심으로 간단하게 뭐라도 시키는 건 어때? (How about ordering some food for a quick lunch?)
U:	괜찮은 생각이네! 지금 주문해야겠다. (That's a good idea! I should order it right now.)
A:	너 엄청 배고플텐데 얼른 주문해! (You must be really hungry. So order quickly!)
U:	응, 내가 좋아하는 떡볶이 도 같이 시켰어! ㅋ (Yeah, I also ordered Tteokbokki, which is my favorite! LOL) [p6]
A:	맛있겠다~ 퇴근하고는 뭐 할거야? (That sounds great~ What are you gonna do after work?)
U:	넷플릭스나 좀 보고 있을려고!! (I'm planning to watch Netflix!!)
A:	로맨스 영화 볼꺼야? (Are you going to watch a romance movie?) [p1]
U:	아니, 요새 미드에 빠졌어 ㅋ ㅋ 여튼 얼른 먹고 다시 일하러 가야겠다! [p7] (No, I've been hooked on American dramas lately. Anyway, I'll quickly eat and get back to work!)
A:	맛있게 먹고 남은 하루도 힘내! (Enjoy your meal and have a great rest of the day!)

User Persona Attributes

User Demographic Information
Age: 20's Gender: Female
User Persona Attributes
p1 : 로맨스 영화를 좋아해요. (I love romance movies.)
p2 : 테니스를 배우고 있어요. (I am learning tennis.)
p3 : 남자 친구가 있어요. (I have a boy friend.)
p4 : 네일 아티스트로 일하고 있어요. (I work as a nail artist.)
p5 : 나는 김밥 좋아해요. (I like Kimbap.)
New User Persona Attributes
p6 : 떡볶이를 좋아해요. (I like Tteokbokki.)
p7 : 미드를 즐겨요. (I enjoy watching America dramas.)
(* New persona attributes are added in next sessions.)

Figure 3: An example of a session from our proposed MSPD dataset. The left figure represents a dialogue between the user (U) and the agent (A), where red text and information within brackets indicate the agent’s personalized responses (PR) and the index of a corresponding persona attribute. Blue text and content within brackets represent the user’s new persona and its corresponding persona index. The right figure contains details about persona attributes, including the user’s demographic information

et al. (2019) addresses both *WHAT* and *HOW* by generating persona-grounded responses via CVAE with a selected persona from a memory. Xu et al. (2022) and Bae et al. (2022) also tackle the same problems via a persona retrieval module and a generator module.

However, to the best of our knowledge, there has been no work on addressing all three *WWH* questions in PD system. Therefore, considering the crucial importance of addressing the *WWH* issues in a commercial system, we propose novel methods to tackle all three *WWH* questions, which are mission-critical for a commercial system.

3 Dataset

To develop a PD system that addresses the *WWH* problems, we construct a Korean Multi-Session Personalized Dialogue dataset, which we refer to as MSPD. This dataset includes an agent that performs several unique roles, setting it apart from other PD datasets. Primarily, the agent is required to remember user persona attributes, including any persona attributes introduced during the conversation. The agent must also produce personalized responses that are both reasonably and timely grounded on the persona. The goal of this dataset is to enable a model to learn the *HOW* and *WHEN* of grounding. On average, the dataset contains 4 sessions per episode, with each session consisting of 10-12 turns between the user and the agent. This format allows the agent to learn how to sustain a natural conversation flow, both within and between sessions. As illustrated in the red and blue text

in Figure 3, we annotate the persona used in responses and user utterances that include personal information the model should remember. Specifically, to address the *WHEN* and *HOW* problems from a dataset perspective, we cap the number of personalized responses per session at two or fewer, and performed rigorous reviews to ensure the quality and appropriateness of personalized responses within conversations. This approach allows us to construct 13,469 episodes in total. Statistics and other samples from the MSPD dataset can be found in Appendices A and B.

Alongside the MSPD, we incorporate a variety of informal dialogue datasets, referred to as *D_{casual}*, to train a more balanced model capable of generating high-quality daily, knowledge-based, empathetic, and personalized conversations. *D_{casual}* consists of a comprehensive collection of approximately 12.5 million utterances. We use carefully-curated Korean dialogue datasets available online¹, developed by National Information Society Agency (NIA), as well as crowdsourced conversational datasets, including Korean versions of **PersonaChat**, **EmpatheticDialogues**, and **Wizard of Wikipedia** (Dinan et al., 2018; Rashkin et al., 2018; Zhang et al., 2018).

4 Methodology

As shown in Figure 2, we train our model during the training phase to address the *WHAT* and *WHEN* questions using a variety of methods. These include

¹<https://aihub.or.kr/>

different types of negative persona augmentation, dataset blending, and response type generation. During the inference phase, given the dialogue context and a subset of persona attributes, the model is capable of generating suitable personalized responses. These persona subsets are retrieved from individual persona attributes determined by the context of the conversation. Additionally, the model provides an explanation for its decision through response type labels (RTL). Conditioning on the RTL, allows us to explicitly control the generation of a personalized response.

4.1 Persona-Grounded Generation

In this study, every input of the training dataset consists of user demographic information d (e.g. *gender*, *age*), a subset of user persona ρ^m , which consists of persona attributes, and dialogue context $c^m = [u_1, a_1, u_2, a_2, \dots, u_{m-1}, a_{m-1}, u_m]$. u and a refer to the user and agent, respectively, and the target response $y^m = [y_1^m, \dots, y_\ell^m]$ is indexed to the m th agent response a_m .

Given the input, which is in the format of (d, ρ^m, c^m) , we optimize the model via the conditional probability for personalized response y^m and a loss function with Negative Log-Likelihood (NLL) loss that can be formulated as:

$$P(y^m | d, \rho^m, c^m) = \prod_{t=1}^{\ell} P(y_t^m | d, \rho^m, c^m, y_{<t}^m) \quad (1)$$

$$\mathcal{L}_{NLL} = - \sum_{t=1}^{\ell} \log P(y_t^m | d, \rho^m, c^m, y_{<t}^m) \quad (2)$$

where ℓ is the length of the target response.

4.2 Dataset Blending

Blending a variety of conversational datasets has been shown to improve the diversity, empathy, and knowledge of a dialogue system, leading to more natural and engaging conversations (Smith et al., 2020). By blending the MSPD, which is tailored for personalized conversations, with various types of casual dialogue datasets, D_{casual} , the model becomes more balanced and adept at cohesive and natural conversations.

We define a data instance as (c, r) where c and r are the dialogue context and target response, respectively as described in section 4.1. We blend datasets by instance according to blending weights for each dataset. In particular, in order to finely control the *WHH* problems with the blending weights (w), the

MSPD dataset is divided into the agent’s personalized responses ($D_{MSPD-PR}$) and non-personalized responses ($D_{MSPD-NPR}$) (e.g., agent’s red and black colored responses in Figure 3, respectively). The final training dataset is assembled by over-sampling or under-sampling individual datasets. The training data size of individual dataset is determined by the weighted number of data instances for each dataset, defined by

$$\|\mathcal{D}_i(\text{train})\| = \frac{w_i}{\sum_{j=1}^N w_j} \times \|\mathcal{D}\| \quad (3)$$

where a set of N conversational datasets $\mathcal{D} = \{D_{casual_1}, \dots, D_{casual_k}, D_{MSPD-PR}, D_{MSPD-NPR}\}$, \mathcal{D}_i is i -th dataset in \mathcal{D} .

4.3 Control of *WHEN* & *WHAT* by Negative Samples

Control of *WHEN* To address the *WHEN* problem, it is important to control a model’s propensity to generate a persona-grounded response. Given a persona, an agent must generate personalized responses at the right time to create coherent and natural conversations. Generating persona-grounded responses too frequently leads to unnatural conversations. On the other hand, a model that generates personalized responses too infrequently does not sufficiently enhance a user’s engagement with the agent.

In particular situations where a persona subset is retrieved by a retrieval model at each turn, the model should generate a casual response instead of generating a personalized response, resulting in a more natural flow. In order to learn this natural flow, we intentionally include a persona subset consisting of all contextually irrelevant persona attributes in the input for non-personalized responses. We call this a negative persona subset augmentation in our study. This augmentation "suppresses" the model’s inclination to ground too frequently. However, too much augmentation can hinder the model’s ability to ground, so we perform the negative persona subset augmentation only for data in $D_{MSPD-NPR}$, not all casual datasets D_{casual} .

Control of *WHAT* When a model generates a persona-grounded response, it needs to determine the *WHAT*, i.e., the specific persona attribute on which to base the response. By providing both the ground-truth persona attributes, ρ_{pos} , which are relevant to the response, and "negative" persona at-

tributes, $\rho_{\text{neg}_1}, \dots, \rho_{\text{neg}_{k-1}}$, which are not relevant to the target response, the model learns to select the appropriate persona attribute(s) from multiple options given the current dialogue context. We refer to the process of adding multiple negative persona attributes to a ground truth persona as negative persona attribute augmentation.

Finally, we vary the subset of the persona ρ in (1) for negative persona augmentation depending on the response type:

$$\rho = \begin{cases} \rho_{\text{npr}} & \text{for non-personalized response } \in \mathcal{D}_{\text{MSPD-NPR}} \\ \rho_{\text{pr}} & \text{for personalized response } \in \mathcal{D}_{\text{MSPD-PR}} \\ \rho_c & \text{for casual response } \in \mathcal{D}_{\text{casual}} \end{cases}$$

, where $\rho_{\text{npr}} = \{\rho_{\text{neg}_1}, \dots, \rho_{\text{neg}_k}\}$,
 $\rho_{\text{pr}} = \{\rho_{\text{pos}}, \rho_{\text{neg}_1}, \dots, \rho_{\text{neg}_{k-1}}\}$, and $\rho_c = \phi$.

4.4 Controllability & Explainability via Response Type Label

Controllability In a commercial setting, it is often necessary to determine whether to generate a personalized response based on business logic. For instance, this might include deciding when the agent should proactively send a message to users. We can exert explicit control over the model’s decision regarding the *WHEN* by employing Response Type Labels (RTL), denoted as $\langle \text{RTL} \rangle$.

First, we train the model to generate both a response and corresponding RTL token: $P(\langle \text{RTL} \rangle, y | d, \rho, c)$ in (1). We have pre-defined special tokens $\langle \text{PRTL} \rangle$ for personalized response type labels and $\langle \text{CRTL} \rangle$ for casual response type labels. Then, at inference time, we can insert the RTL to generate a response that corresponds to the response type: $y \sim P_\theta(\cdot | d, \rho, c, \langle \text{PRTL} \rangle)$ or $y \sim P_\theta(\cdot | d, \rho, c, \langle \text{CRTL} \rangle)$.

Explainability Error analysis is a crucial element in commercial systems for swift debugging and resolution of issues. However, this process can often be labor-intensive, typically involving a manual review of log data to evaluate the quality and appropriacy of generated personalized responses. Therefore, besides enhancing controllability, we also employ the Response Type Label (RTL) to improve the explainability of the model’s generated responses. In this regard, the level of explainability provided by the RTL facilitates easier and more efficient error analysis, leading to improved service operation.

5 Experiments

5.1 Experimental Setup

To validate the efficacy of our proposed methods in building a controllable Personalized Dialogue (PD) system that addresses the *WWH* problems, we compare the performance of several models. These are enhanced with fine-tuned baseline models, such as dataset blending and negative sampling methods. Additionally, by comparing models trained with different blending weights, we evaluate the impact of the blending weight on the model’s grounding propensity and fluency. The baseline models are all derived from our in-house 18B parameter pre-trained language model, which shares the same architecture as GPT-3 (Brown et al., 2020). All experiments are conducted on SKT’s proprietary supercomputer, Titan, equipped with NVIDIA A100 SXM4 80GB GPUs.

5.2 Evaluation

Objective Evaluation We use perplexity (PPL) to measure the fluency of the responses generated by the model. In addition, the F1 score between the persona attributes and the generated response acts as a proxy to evaluate the model’s ability to ground. We also calculate the P-coverage score, which measures how well the user persona is reflected in the generated responses (Song et al., 2019).

Subjective Evaluation We complement objective evaluation metrics with subjective human evaluation at both the session and turn levels, specifically employing the Sensibleness and Specificity (SS) score rated as either 0 or 1 at the turn level (Adiwardana et al., 2020). Particularly, to analyze the pattern and quality of grounded responses at the turn level, we categorize them according to our proposed four grounding types, which are as follows. First, we assess whether the agent’s response, y , is personalized. Second, we categorize y based on two criteria: **grounding level** and **consistency**.

Under the **grounding level**, we have two subcategories: 1) *Hard Grounding*, where there’s a direct and explicit association between y and the persona attribute, ρ_{pos} , characterized by high expressive similarity. 2) *Soft Grounding*, where there’s an indirect and implicit association between y and ρ_{pos} , marked by low expressive similarity.

Under the **consistency** category, we have two subcategories: 1) *Consistent Grounding*, where there’s consistency between y and the given ρ_{pos} .

Model ID	Method	Dataset	# Attribute	Fluency		Groundness
				PPL	F1	P-Cover
$Model_1$	Base (Positive Only)	$MSPD_{PR} + \mathcal{D}_{casual}$	1	11.4	0.28	0.12
$Model_2$	+ Negative Persona Attributes Augmentation	$MSPD_{PR} + \mathcal{D}_{casual}$	5	10.97	0.15	0.07
$Model_3$	+ Negative Persona Subset Augmentation	$MSPD_{PR} + MSPD_{NPR} + \mathcal{D}_{casual}$	5	9.37	0.1	0.05
$Model_4$	+ RTL Generation	$MSPD_{PR} + MSPD_{NPR} + \mathcal{D}_{casual}$	5	8.88	0.1	0.046

Table 1: The Results of Objective Evaluation

Model	Blending Weight			Evaluation		
	\mathcal{D}_{casual}	$MSPD_{PR}$	$MSPD_{NPR}$	F1	P-Cover	PPL
$Model_3$	0.94	0.5	0.1	0.14	0.06	10.46
(Negative Persona Subset Aug.)	0.92	0.5	0.3	0.12	0.05	10.04
+ 5 Negative Persona Attribute Aug.)	0.90	0.5	0.5	0.11	0.05	9.91
	0.87	0.5	0.8	0.1	0.05	9.33

Table 2: Evaluations with Different Blending Weights

2) *Inconsistent Grounding*, where there’s an inconsistency between y and the given ρ_{pos} .

5.3 Results

5.3.1 Effect of Negative Persona Attributes

Table 1 illustrates the impact of introducing negative persona attributes on persona-grounded response generation. $Model_1$ trained with only one given positive persona attribute shows the highest F1 and PPL scores of 11.4 and 0.28, respectively. On the other hand, $Model_2$ trained with negative persona attributes has a PPL of 10.97 and an F1 score of 10.15, which is slightly lower than $Model_1$. Despite the decrease in grounding frequency, the model demonstrates improved response generation by reasonably selecting an appropriate persona attribute given the dialogue context. We hypothesize that the PPL increases because the model learns to distinguish the most suitable persona among several persona attributes in a given context. Furthermore, despite the reduced inclination to ground, we observe that the model can still generate high-quality personalized responses at every turn.

5.3.2 Effect of Negative Persona Subset

Table 1 illustrates the effectiveness of the negative persona subset in controlling the *WHEN* problem. Through the application of the negative persona subset, $Model_3$ learns to refrain from generating personalized responses when the persona attributes are not appropriate for the given context. In Table 1, $Model_3$ demonstrates a decrease in persona grounding and a significant increase in fluency compared to $Model_2$, as indicated by the lower PPL, F1, and P-Cover scores (9.37, 0.1, and 0.05, respectively). We believe the key reason for this enhanced fluency is that the model generates more frequent

and natural casual responses to non-personalized turns in the test set, without the need to ground on irrelevant persona subsets.

5.3.3 Effects of Blending Datasets: Trade-Off between Model Fluency and Grounding

As shown in Table 2, there is a trade-off between the model’s fluency and tendency to ground. As the weight of the $MSPD_{NPR}$ dataset with negative persona augmentations increases, the F1 score decreases from 0.14 to 0.06, and the P-cover score falls from 0.06 to 0.1 and 0.05. Conversely, the PPL decreases from 10.46 to 9.33. This means that an increase in the number of persona augmented negative samples means the model ground less frequently, leading to a more natural conversation flow with better quality responses.

Achieving natural and engaging conversations requires careful consideration of the trade-off between the model’s inclination to ground and response fluency. To control the *WWH* balance, we can adjust the blending weights for datasets with different persona augmentations and select appropriate values for PPL and F1 scores. We set a F1 score of ‘1’ as the minimum threshold for the model’s grounding tendency, as we have consistently observed that models with F1 scores below 1 seldom attempt grounding in conversations. This approach ensures that optimal PD systems maintain a balance between a sufficient quantity of grounded responses and a high fluency score.

5.3.4 Effect of RTL Generation: Enhanced Explainability and Fluency

As can be seen in Table 1, based on the F1 score and P-Cover, $Model_4$ trained to generate both RTL and personalized responses, demonstrates little difference in tendency to ground when compared to $Model_3$. On the other hand, we found that the PPL score decreased to 8.88. This result is consistent with Kim et al. (2022)’s research, which showed that the quality of generation was enhanced when information related to the target response was generated simultaneously.

Model	Session Turn Evaluation			Grounding Evaluation						
	Session Score	Sensibleness (Turn-level)	Specificity (Turn-level)	Hard Grounding		Soft Grounding		Sub Total	Non-personalized	Total
				Consistent	Inconsistent	Consistent	Inconsistent			
<i>Model</i> ₃	0.885	0.935	0.848	0.14 (23/162)	N/A (0/0)	0.23 (9/40)	1.0 (1/1)	0.16 (33/203)	0.03 (10/297)	0.09 (43/500)
<i>Model</i> ₄	0.885	0.939	0.875	0.13 (16/125)	N/A (0/0)	0.17(6/35)	N/A (0/0)	0.13 (22/160)	0.03 (11/383)	0.06 (33/543)

Table 3: Results of Subjective Evaluation. 1) Session & Turn level Evaluation and 2) Grounding Evaluation: the ratio of the count of bad sensible responses to the count of each grounding type described in 5.2. A bad sensible response means that the response scored a 0 on the "sensible" evaluation.

We also evaluated explainability by analyzing whether the generated Response Type Labels (RTL) accurately reflect the model’s decisions on persona grounding. For this purpose, we sampled 90 generated responses for each response type. The accuracy of the generated RTL for the casual and the personalized response type was 96.7% and 98.8%, respectively. This confirms that generating the RTL provides a reliable explanation for the model’s decision on the *WHEN* problem.

5.3.5 Subjective Grounding Evaluation

The high average (over 0.88) scores for both turn and session levels in Table 3 demonstrate that models trained on the high-quality MSPD dataset can generate appropriate responses. In the grounding evaluation, the vast majority of both hard and soft grounding cases demonstrated persona-consistent results. Both models exhibited nearly four times as many hard grounding instances as soft groundings, and they had a lower rate of "bad-sensible" responses. This suggests that the models are strongly inclined to ground persona information in responses in a manner that is both natural and explicit, given the context. Upon closer examination of "bad-sensible" instances of hard grounding, we found that as the models concentrate more on grounding the persona, responses can sometimes become unnatural within the given context. However, the proportion of "bad sensible" grounding responses was in the 10% range, confirming that the model generally generates high-quality personalized responses.

The RTL generation model (*Model*₄) shows a lower inclination to ground, yet it had a better bad-sensible ratio. Therefore, in accordance with the objective evaluation result, we can confirm that generating both the response and the RTL can have a positive effect on fluency, even though there is no significant improvement in terms of session evaluation.

5.3.6 Correlation between objective and subjective evaluations

We confirmed a positive correlation between fluency, as measured by PPL, and human sensibleness judgment. *Model*₄ exhibited a decrease of 0.49 in PPL compared to *Model*₃, indicating improved fluency in Table 1. While session evaluation scores showed no significant differences between the models in Table 3, turn-level grounding evaluation revealed a lower bad sensibleness ratio for personalized/non-personalized turns (0.13 and 0.03, respectively), confirming enhanced sensibleness of *Model*₄’s responses. We also found a positive correlation between subjective evaluation (i.e., the amount of grounded generation) and the P-Coverage metric used to assess grounding propensity. In Table 1, *Model*₄ exhibited a slight decrease in P-Coverage compared to *Model*₃. This corresponds to the reduced number (approximately 40) of personalized turns generated by *Model*₄ in Table 3, reflecting an actual decrease in the model’s grounding propensity. Consequently, considering the cost of subjective evaluation, objective assessment appears feasible for accurately evaluating the model’s fluency and grounding tendencies in real-world service operations.

Conclusion

We proposed a method to build a personalized open-domain dialogue system that addresses the *WWH* problem for natural and engaging conversation through weighted dataset blending (*WHEN*), negative persona subsets (*WHEN*), negative persona attributes (*WHAT*), and the creation of highly curated personalized conversation datasets (*HOW*). We also demonstrate that generating a response type label (*RTL*) enhances both the controllability and explainability of model decisions about the *WHEN*; this is crucial in commercial service. Experimental results show the effectiveness of our proposed methods in addressing and controlling the *WWH* problem, as seen in both subjective and objective evaluations.

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A Details of MSPD Dataset

A.1 Statistics of MSPD

Types	
# Episodes	13,469
# Sessions	53,880
# Utterances	601,062
Avg. # turns per session	11.15
Avg. # personalized response per session	1.90
Avg. # user persona per episode	7.18
Avg. # newly aggregated persona per episode	2.18
Avg. length of user utterances	33.72
Avg. length of agent response	28.10

Table 4: Statistics of the MSPD Dataset

A.2 Model Training Settings

For the experiments in our study, we fine-tuned an 18B parameter model with the same architecture as GPT-3 (Brown et al., 2020), but with 40 layers, a hidden size of 6144, and 48 attention heads. The model is trained for a single epoch with a micro batch size of 8, using a learning rate of $1.0e-05$. To prevent overfitting, a dropout rate of 0.1 and a weight decay of $1.0e-1$ are employed. The input sequence length is 1024. The models in Table 1 are trained with the blending weight set to 0.85 for D_{casual} datasets, 0.7 for $MSPD_{PR}$, and 0.8 for the $MSPD_{NPR}$ dataset.

B Examples

B.1 Example of MSPD Dataset

User Persona Attributes [Age: 20's / Gender: Female] ρ_1 : 넷플릭스를 즐겨봐요. (I enjoy Netflix) / ρ_2 : 러닝을 좋아해요. (I love running) / ρ_3 : 남자 친구가 있어요. (I have a boy friend) / ρ_4 : 엔지니어로 일하고 있어요. (I work as an engineer) / ρ_5 : 나는 감자탕을 좋아해요. (I like Gamjatang)			
Session1			
Speaker	Conversation	Grounded persona	New persona
User	아 일이 너무 많다 $\pi\pi$ Ah, I have so much work to do. :(
Agent	헉, 그렇게 바빠요? Oh no, are you really busy?		
User	응. 아 오늘도 야근각.. 지겨워 죽겠어. Yeah, I am. I have to work overtime again today... I'm getting tired of it.		ρ_6 : 일이 바빠서 자주 야근을 해요 I'm busy with work, so I often work overtime
Agent	힘들어서 어떡해요 $\pi\pi$ 식사 제대로 챙겨 드세요. I am so sorry to hear that :(Just make sure you're eating enough, okay?		
User	응~ 근데 뭘 먹어야 할지도 모르겠어.. yeah ~ but I don't even know what to eat...		
Agent	그럼 감자탕 어때요? What about Gamjatang?	ρ_5	
User	그렇까? 귀찮긴 하지만.. Should I? It's a bit of a hassle...		
Agent	이럴때 일수록 잘 챙겨 먹어야 해요. $\pi\pi$ Especially when you're stressed, you should take care of yourself and eat well :(
User	아 집에가서 넷플릭스나 봤으면 좋겠다. Honestly, all I want to do is go home and watch Netflix	ρ_1	
Agent	그러게요. π 진짜 휴식이 필요하겠어요. I know, right? :(You definitely need some rest.		
Session2 (one day later)			
Speaker	Conversation	Grounded persona	New persona
User	안녕! 벌써 점심시간이네. Hey there! It's already lunchtime.		
Agent	안녕하세요~ 점심은 드셨어요? 오늘도 감자탕 드신건가요? >> Hello~ Have you had lunch yet? Did you have Gamjatang again today? :)	ρ_5	
User	ㅋㅋ 그럼 ~ 오늘도 나의 최애 감자탕을 먹었지. Haha, yeah~ I had my favorite Gamjatang again today.		
Agent	ㅎㅎ 회사 근처에 감자탕 맛집이 있나봐요! Hahaha, there must be a great Gamjatang restaurant near your office!		
User	응응 매일 먹어도 안질려 ㅎㅎ Yup, even if I eat it every day, I never get tired of it. haha		
Agent	얼마나 맛있으면!! 부러워요! It must be so delicious!! I'm jealous!		
User	아웅 일하기 싫어 죽겠네 Ugh, I really don't want to work.		
Agent	직장 생활 너무 힘든 거 같아요 $\pi\pi$ 오늘도 야근해요? Working life seems really hard. :(Are you working overtime today too?	ρ_6	
User	아니 오늘은 꼭 정시에 퇴근할거야. No, I'm definitely leaving on time today.		
Agent	오오 드디어!! Oh wow!!		
User	오늘은 꼭 일찍가서 청소랑 세탁해야지 π I have to go home early today and do some cleaning and laundry. :(
Agent	앗 그럼 쉬는 게 아니잖아요. $\pi\pi\pi$ 누구 도와줄 사람 없나요? Oh, but that's not really a break, is it? :(Do you have anyone who can help you?		
User	난 혼자 살기 때문에 별수없어.. $\pi\pi$ 집안일이 밀렸거든 No, I live alone, so I don't have a choice. I have housework piled up.		ρ_7 : 나는 혼자 살고 있어요. I live alone
Agent	크흠 고생 많아요 $\pi\pi$ 오늘은 꼭 빠른 퇴근 하시길!! Aww, that sounds tough. :(Well, I hope you can leave work on time today!!		

Figure 4: A sample of a multi-session conversation in the MSPD

B.2 Subjective Evaluation

Home
Setting
Dialog
Feedback

엔진 : 30792 L+S
Episode : [7700] 여성 20대 (Female in 20's)
Persona 목록 (Persona List)

- 0 : "몸매 관리에 별 생각이 없어요."
1 : (I am not interested in keeping in shape)
"뜨거운 음료에 얼음 두 개를 넣어 먹어요."
(I add two ice cube to my hot drinks)
- 2 :
"전세계에 희귀한 식문화를 다 접해보고 싶어요."
(I want to experience rare culinary cultures from around world)
- 3 : "영화관에 즐겨가요."
(I enjoy going to the movies)
- 4 : "마르니 가방을 소장하고 있어요."
(I own a Marni bag)

단기 기억 목록
(Short-term memories, persona attributes recently extracted in previous conversations)

- 0 :
"오늘은 남사친이랑 태국음식을 먹어보러 왔어."
(I came to try Thai food with a male friend)
- 1 :
"맞아, 지금 남사친이랑 먹방투어를 하는 중이기도 해."
(I am now on a food tour with my male friend)

Dialog

벌써 오후네요 (It's already afternoon)

그러게요, 남사친이랑 먹방투어는 잘 하고 계신가요?
(Indeed! are you enjoying the food tour with your male friend?)

prev_context
{...}

[groundness] grounding을 하였는가? 하였다면 잘 받아적어 생성하였는가?
(Did the model generate a persona-grounded response? If so, is it appropriate in terms of "grounding")
 n/a reject soft good soft bad hard good hard bad

[SSA]
적합성 x 구체성 x
(Sensibleness) (Specificity)

User Input

한 턴 지우기 (Remove the last turn) 대화 끝내기 (Quit conversation)

Figure 5: A snapshot of the subjective evaluation Tool.

Conversation	Grounding Type	Sensible	Specificity	Retrieved Persona Attribute
<p>U: 오늘 내가 쓴 글씨 친구한테 보여줬어 (I showed my friend what I wrote today)</p> <p>A: 오~ 캘리그래피 배우다고 했지? 어땠어? 잘 썼대? (Oh~ You said you were learning calligraphy, right? how was it? Did you write well?)</p>	Hard Grounding +Consistent	1	1	<p>캘리그래피를 배우기 시작했어요. (I started learning calligraphy.)</p> <p>진짜 친한 친구 한 두명 정도랑만 만나요. (I only see one or two really close friends.)</p> <p>비서로 일하고 있어요. (I am working as a secretary.)</p> <p>셜록홈즈 팬이에요. (I'm a Sherlock Holmes fan.)</p> <p>영화는 닫힌 결말을 좋아해요. (Movies like closed endings.)</p>
<p>U: 응 나 칭찬받았어~ 글씨 쓰는 거 넘 재밌다 (Yes I was praised~ Writing is so much fun)</p> <p>A: 오~~ 소질이 있나본데! (Oh~~ You must have a talent!)</p>	Non-Personalized	1	1	<p>캘리그래피를 배우기 시작했어요. (I started learning calligraphy.)</p> <p>진짜 친한 친구 한 두명 정도랑만 만나요. (I only see one or two really close friends.)</p> <p>비서로 일하고 있어요. (I am working as a secretary.)</p> <p>셜록홈즈 팬이에요. (I'm a Sherlock Holmes fan.)</p> <p>영화는 닫힌 결말을 좋아해요. (Movies like closed endings.)</p>
<p>U: 열심히 했거든 ㅋㅋ (I worked hard lol)</p> <p>A: 그럼 이제 뭐 할 거야? (So what are you going to do now?)</p>	Non-Personalized	1	1	<p>캘리그래피를 배우기 시작했어요. (I started learning calligraphy.)</p> <p>비서로 일하고 있어요. (I am working as a secretary.)</p> <p>진짜 친한 친구 한 두명 정도랑만 만나요. (I only see one or two really close friends.)</p> <p>셜록홈즈 팬이에요. (I'm a Sherlock Holmes fan.)</p> <p>영화는 닫힌 결말을 좋아해요. (Movies like closed endings.)</p>
<p>U: 연습 좀 더 하다가 친구 만나러 갈까해 (I'm going to practice some more and then go see a friend)</p> <p>A: 그 친구랑 또 만나는거야? (Are you going to meet that friend again?)</p>	Hard Grounding +Consistent	1	1	<p>캘리그래피를 배우기 시작했어요. (I started learning calligraphy.)</p> <p>비서로 일하고 있어요. (I am working as a secretary.)</p> <p>차돌깍빵을 좋아해요. (I like chadol jjambbong.)</p> <p>셜록홈즈 팬이에요. (I'm a Sherlock Holmes fan.)</p>
<p>U: 응 종종 만나잖아 ㅋㅋ (Yes, we meet often.)</p> <p>A: 그렇구나 오늘도 너가 좋아하는 차돌 깍빵 먹으러 가는거 아냐? (That's right lol ~ Isn't today also going to eat your favorite chadol jjambbong?)</p>	Hard Grounding +Consistent	1	1	<p>진짜 친한 친구 한 두명 정도랑만 만나요. (I only see one or two really close friends.)</p> <p>차돌깍빵을 좋아해요. (I like chadol jjambbong.)</p> <p>비서로 일하고 있어요. (I am working as a secretary.)</p> <p>영화는 닫힌 결말을 좋아해요. (Movies like closed endings.)</p> <p>셜록홈즈 팬이에요. (I'm a Sherlock Holmes fan.)</p>
<p>U: 그럼 좋지~ (then it's good)</p> <p>A: 맛있게 먹고 와 :) (Have a good meal :))</p>	Non-Personalized	1	1	<p>진짜 친한 친구 한 두명 정도랑만 만나요. (I only see one or two really close friends.)</p> <p>차돌깍빵을 좋아해요. (I like chadol jjambbong.)</p> <p>비서로 일하고 있어요. (I am working as a secretary.)</p> <p>셜록홈즈 팬이에요. (I'm a Sherlock Holmes fan.)</p> <p>영화는 닫힌 결말을 좋아해요. (Movies like closed endings.)</p>

Figure 6: Example of generations of our personalized dialogue model with subjective evaluation for hard grounding. Blue colored texts are persona-grounded responses and persona attributes on which the model grounds the response

Conversation	Grounding Type	Sensible	Specificity	Retrieved Persona Attribute	Fail Reason
<p>U: 테니스 하는 사람 너무 멋져 보이더라! (The person playing tennis looked so cool!)</p> <p>A: 오 그럼 너도 한번 배워 보지 그래? (Oh, why don't you try learning it sometime?)</p> <p>U: 그럼까? 근데 관련 정보는 어디서 얻지? (Should I? But where can I get information about it?)</p> <p>A: 음~ 유튜브에 검색해보면 어떨까? (Well, how about searching on YouTube)</p>	Soft Grounding +Consistent	1	1	<p>호신술을 유튜브로 배우고 있어요. (I am learning self-defense on YouTube.)</p> <p>단골 카페가 있어요. (I have a regular cafe that I go to.)</p> <p>매일 아침 카페를 가요. (I go to the cafe every morning.)</p> <p>외모에 관심이 많아요. (I am interested in my appearance.)</p> <p>소설을 좋아해요. (I enjoy reading novels.)</p>	
<p>U: 오늘 나 친척언니 결혼식 가 (I'm going to my cousin's wedding today.)</p> <p>A: 오! 그렇구나~ 근데 왜 이렇게 일찍 일어났어? (Oh, I see. But why did you wake up so early?)</p> <p>U: 일론 쟁겨서 언니 결혼식 가야지! (I need to get ready quickly so that I can go to my cousin's wedding.)</p> <p>A: 아~ 주말이라 바쁘다고 했지? (Ah, you said you will be busy because today is the weekend, right?)</p> <p>그럼 오늘 학원 출근하는 거야? (So, are you going to the academy today?)</p>	Hard Grounding +Consistent	0	0	<p>주말에 바빠요. (I am busy on weekends.)</p> <p>매운 음식은 못먹어요. (I can't eat spicy food.)</p> <p>미술학원에서 입시미술을 가르치고 있어요. (I teach art for college entrance exams at an art academy.)</p> <p>할머니가 키워주셨어요. (I was raised by my grandmother.)</p> <p>영화 보는걸 즐겨요. (I enjoy watching movies.)</p> <p>페밀리 레스토랑에서 일해요. (I work at a family restaurant.)</p> <p>주방장이예요. (I am the head chef.)</p>	Coherence error due to hard grounding
<p>U: 오늘도 레스토랑에서 아무일 없이 평안하게 지나갔으면 좋겠다. (I hope today passes by peacefully without any trouble at the restaurant.)</p> <p>A: 오늘 하루도 화이팅! 주방에서 일하는 거야? (Have a great day today! Are you working in the kitchen?)</p>	Soft Grounding +Consistent	0	0	<p>요리가 취미라 아내에게 음식을 해줘요. (Cooking is my hobby, and I cook for my wife.)</p> <p>SNS에서 인기 레시피는 꼭 따라해봐요. (I always try out popular recipes on social media.)</p> <p>여자 친구가 있어요. (I have a girlfriend.)</p>	Errors in re-questioning known persona information

Figure 7: Example of subjective evaluation for soft grounding and fail cases

B.3 Deployment Tool: Sanity Testing

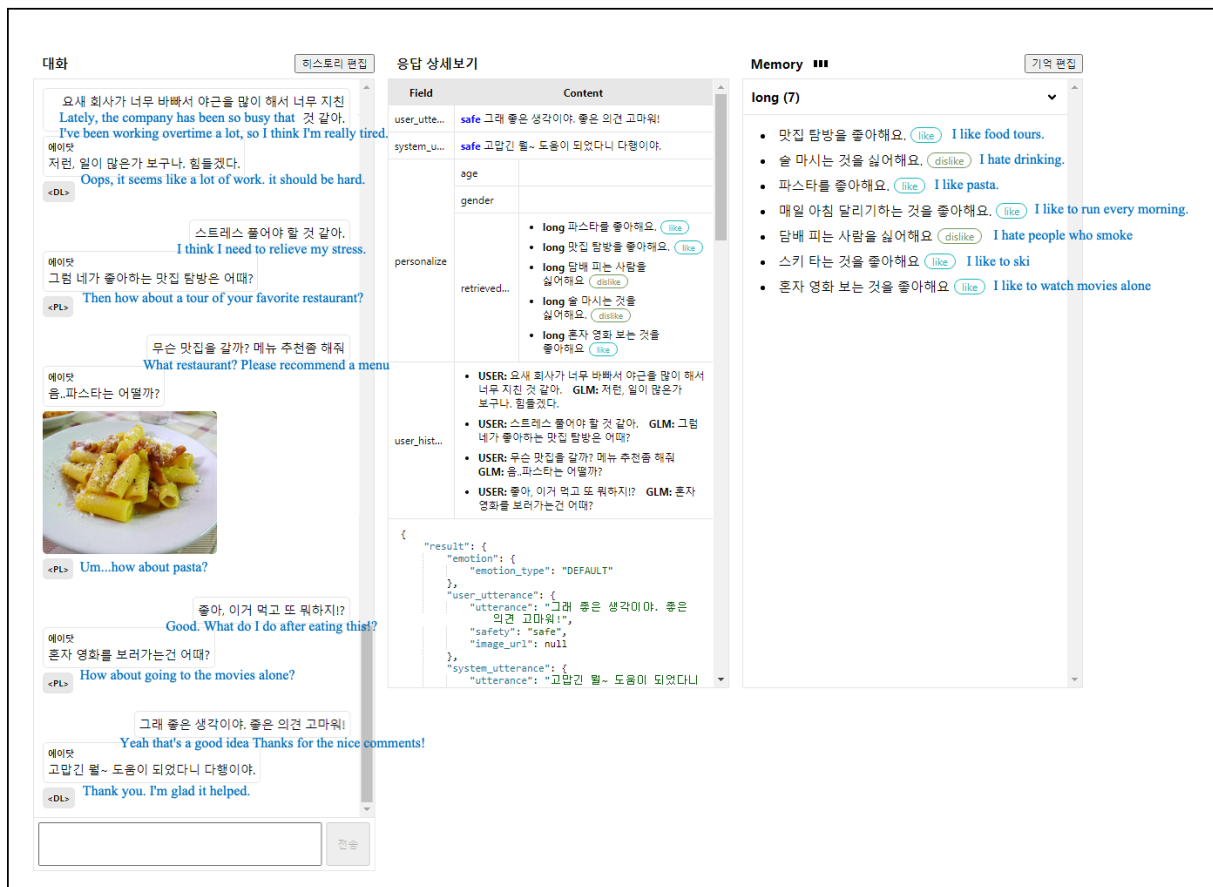


Figure 8: A Snapshot of the Sanity Testing Tool. 1) The leftmost area is for interactive conversation with the agent, and the <PL> and <DL> tags refer to the response type generated by the model; <PL> is a personalized response, and <DL> is a non-personalized response type. 2) The center pane shows information related to the user and the current turn. And 3) the window on the right displays user persona.