Grouped Simulator: Bridging Group Homogeneity and Individual Heterogeneity for High-Fidelity User Simulation

Anonymous ACL submission

Abstract

High-fidelity user simulation is critical for optimizing downstream multi-turn conversational applications such as telemarketing and automated customer service. Current approaches based on Large Language Models typically employ role-playing via prompting, relying on coarse-grained profiles and internal knowledge to guide behavior generation. However, a realistic simulation requires the simultaneous modeling of group homogeneity and individual heterogeneity. The former refers to shared fine-grained behavioral patterns within a user cohort, while the latter represents the diverse preferences and expression styles of distinct users. Existing paradigms struggle to meet this dual requirement, failing to capture nuanced group commonalities while being insufficient in personalized diversity. To address these limitations, we propose the Grouped Simulator, a framework designed to bridge group homogeneity and individual heterogeneity. We implement a dual-optimization strategy: (1) Group-Aligned Reinforcement Learning with multi-level reward to internalize shared behavioral patterns, and (2) a Retrieval-Augmented Dynamic SOP Engine to inject diverse, context-aware individual feedback. Experiments on a telemarketing benchmark demonstrate that Grouped Simulator significantly outperforms competitive baselines in terms of realism and diversity. [1].

1 Introduction

The advancement of Large Language Models (LLMs) (OpenAI et al., 2024b; Touvron et al., 2023; Qwen et al., 2025) has evolved user simulation from rigid rule-based systems into dynamic agentic frameworks(Ren et al., 2024; Wu et al., 2025). User simulation is crucial for multi-turn conversational systems, particularly in domains like telemarketing and customer service, where training directly with human users is often costly and risky. Therefore, high-fidelity user simulators provide an essential environment to optimize strategies and evaluate agent performance prior to deployment (Liu et al., 2024; Bougie and Watanabe, 2025).

Current approaches predominantly employ LLMs to simulate users via role-playing, relying on coarse-grained static prompts or fine-tuning (Naous et al., 2025; Wang et al., 2025). Even with domain adaptation, these methods fundamentally depend on static instructions and internal parametric knowledge during deployment, failing to capture the dual nature of realistic user behavior: Group Homogeneity and Individual Heterogeneity. First, group homogeneity refers to the shared behavioral patterns within a specific user cohort. For instance, customers in telemarketing scenarios often exhibit collective defensiveness or impatience. However, LLMs aligned via Reinforcement Learning from Human Feedback (RLHF) typically prioritize helpfulness and compliance, hindering the simulation of such realistic, often non-cooperative behaviors(Lin et al., 2024; Sharma et al., 2024; Wei et al., 2023). Second, individual heterogeneity refers to diverse preferences and styles among distinct users. Even within the same customer cohort, reactions vary significantly; a price-sensitive customer might bargain extensively, while a busy individual may terminate the call abruptly. Existing models often suffer from an averaging effect, capturing the corpus mean rather than individual variance (Zhang et al., 2025a). This limitation exacerbates in multi-turn dialogues, leading to model collapse that erodes persona consistency and dynamic strategies (Laban et al., 2025).

To address these challenges, we propose GROUPED SIMULATOR, a unified framework designed to bridge group homogeneity and individual heterogeneity, as illustrated in Figure 1. To build the data foundation, we first introduce an

[1] Code: https://anonymous.4open.science/r/E630.

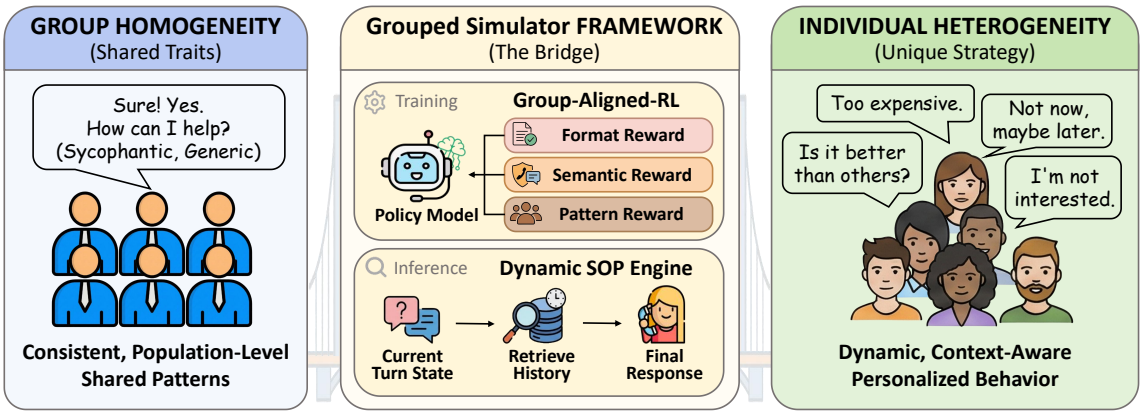


Figure 1: Overview of GROUPED SIMULATOR bridging group homogeneity and individual heterogeneity.

automated data pipeline to extract user profiles and behavioral chains from multi-turn conversation datasets. Then we employ a dual-strategy mechanism: (1) To capture group homogeneity, we introduce **Group-Aligned Reinforcement Learning**. We design a multi-level reward mechanism that provides feedback ranging from surface-level formatting to deep semantic styles, steering the model to internalize shared behavioral patterns. This mechanism effectively counteracts the inherent helpfulness bias, enabling the reproduction of realistic group behaviors. (2) To ensure individual heterogeneity, we propose a **Retrieval-Augmented Dynamic SOP Engine**. We established a mapping library that links user profiles to specific behavioral chains. During interaction, this engine explicitly injects historical reference behaviors conditioned on the current turn state, dynamically guiding the simulator to maintain distinct persona traits. This approach circumvents the averaging effect, ensuring diverse and consistent persona realization even across long-horizon interactions.

To validate our approach, we conduct experiments within telemarketing scenarios. This high-value domain is characterized by distinct collective resistance and diverse individual strategies. We establish a hybrid evaluation protocol integrating both subjective alignment assessment and objective diversity analysis. We utilize GPT-4o (OpenAI et al., 2024a) to assess adherence to profile constraints and business realism (Zheng et al., 2023; Chan et al., 2023), complemented by statistical metrics to quantify turn-level variability. Empirical results demonstrate that GROUPED SIMULATOR significantly outperforms baselines, particularly in capturing business realism and mitigating the mode collapse observed in static simulation approaches.

In summary, this paper makes three key contributions:

- We propose a novel user simulation framework for high-friction proactive dialogue that jointly models homogeneity and heterogeneity. By integrating Group-Aligned RL with the Dynamic SOP Engine, our approach effectively alleviates both assistant bias and the limitations of static personas in telemarketing scenarios.
- We design an automated pipeline to extract user profiles and behavioral chains from multi-turn conversations, reducing reliance on manually curated domain knowledge.
- We propose a hybrid evaluation protocol that combines subjective alignment and objective diversity metrics to rigorously validate simulation fidelity across diverse user profiles.

2 Telemarketing Scenarios

This section formally defines the user simulation task in telemarketing and establishes a framework specifically for evaluating the simulator.

2.1 Task Definition

We formulate the user simulation as a constrained conditional sequence generation task. Let $H_t = \{u_1, r_1, \ldots, u_t\}$ denote the dialogue history at turn t, where u_i and r_i represent the sales agent's utterance and the simulator's response, respectively. The simulator aims to generate the next response r_t conditioned on H_t, an explicit customer profile $\mathcal{P}$, and a reference Dialogue SOP chain $\mathcal{G}$. Here, SOP refers to retrieval-based behavioral trajectory guidance rather than a rigid operating procedure.

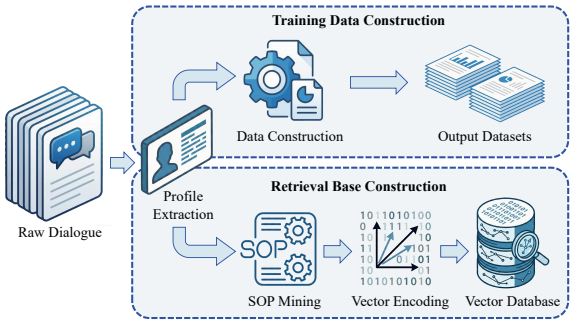


Figure 2: The dual-stream data construction pipeline. **Stream I** (top): Profile extraction generates $\mathcal{D}_{gen}$ and $\mathcal{D}_{sim}$. **Stream II** (bottom): SOP mining builds the hierarchical vector database $\mathcal{M}_{SOP}$.

Formally, we model the response generation by maximizing the conditional probability:

$$r_t^* = \underset{r_t}{\operatorname{argmax}}\, P_\theta(r_t \mid H_t, \mathcal{P}, \mathcal{G}), \tag{1}$$

where θ denotes the model parameters. Unlike standard dialogue generation, the objective requires both linguistic coherence and strategic traversal of $\mathcal{G}$, adapting the trajectory to maximize coverage of valid SOP nodes as the conversation evolves.

2.2 Evaluation Framework

We establish a hybrid evaluation protocol integrating both subjective alignment assessment and objective diversity analysis.

2.2.1 Subjective Alignment Assessment

We employ GPT-4o as an impartial evaluator to score the simulator on a 0-10 Likert scale. The assessment focuses on three core dimensions corresponding to our design objectives:

- **Profile Consistency**(S_{PC}) measures Category Alignment (Cat.) and Profile Adherence (Pro.) to verify whether the simulator faithfully adheres to its assigned persona attributes.
- **Business Realism**(S_{BR}) assesses the authenticity of the customer tone via Brevity(Bre.), Naturalness (Nat.), and Contextual Immersion (Con.), ensuring the mitigation of standard helpfulness bias.
- **Interaction Logic**(S_{IL}) evaluates Intent Responsiveness (Int.) and Logical Consistency (Log.) to ensure coherence and relevance.

The detailed prompts used for these assessments are provided in Appendix F.

2.2.2 Objective Diversity Analysis

To quantify behavioral diversity and verify that the model avoids mode collapse, we introduce three statistical metrics.

Turn-level Length Variability (TLV). We compute the variance of response lengths to capture conversational rhythm:

$$\text{TLV} = \frac{1}{T}\sum_{t=1}^{T}(\ell_t - \bar{\ell})^2, \tag{2}$$

where ℓ_t denotes the length of response r_t and $\bar{\ell}$ represents the mean response length.

Inter-turn Redundancy Suppression (IRS). To quantify the avoidance of repetitive patterns, we measure the semantic dissimilarity between adjacent responses:

$$\text{IRS} = 1 - \frac{1}{T-1}\sum_{t=2}^{T}\Big(\cos\big(\phi(r_t), \phi(r_{t-1})\big)\Big), \tag{3}$$

where $\phi(\cdot)$ denotes the sentence encoder used to extract semantic features.

SOP Node Richness (SNR). We track the coverage of distinct Standard Operating Procedure (SOP) nodes to evaluate the simulator's ability to traverse diverse conversational stages:

$$\text{SNR} = \frac{|\{z_t\}_{t=1}^{T}|}{|\mathcal{S}|}, \tag{4}$$

where z_t is the SOP node at turn t and $|\mathcal{S}|$ is the total number of defined SOP nodes.

3 Methodology

In this section, we present the proposed framework. First, we introduce the data construction pipeline that transforms raw dialogue into high-quality instruction datasets and a retrieval base. Second, we detail the GROUPED SIMULATOR architecture, which consists of the Persona Generation Module and the Simulation Core Module. Finally, we describe the overall inference workflow.

3.1 Dual-Stream Data Construction Pipeline

The foundation of GROUPED SIMULATOR lies in high-quality, profile-centric data. As illustrated in Figure 2, we devise a dual-stream pipeline anchored by a shared profile extraction phase. Following Wang et al. (2025), we first infer implicit

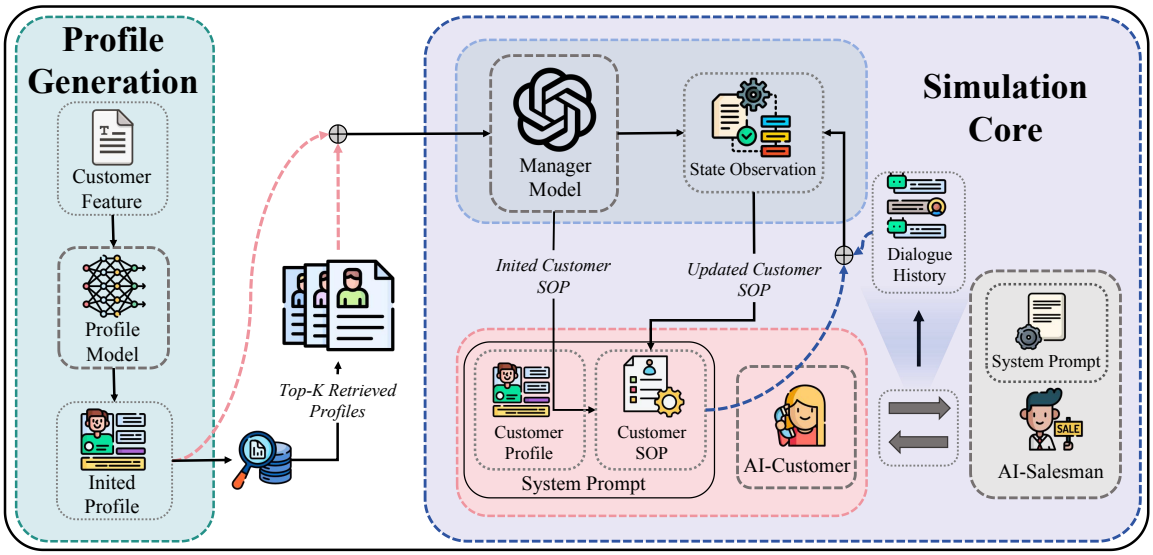


Figure 3: The architecture of the proposed Grouped Simulator, an end-to-end intelligent user simulator framework.

customer profiles p from raw dialogue $\mathcal{D}_{raw}$, which then anchor subsequent data streams.

The first stream synthesizes training data to equip the model with profiling and role consistency. To generate diverse customer profiles from scratch, we curate a profile-generation dataset $\mathcal{D}_{gen}$ and cast it as an instruction-following task:

$$\mathcal{D}_{gen} = \{(I_{gen}, p)\}, \tag{5}$$

where I_{gen} denotes the instruction "generate a customer profile" and p is the extracted ground-truth profile.

To enforce persona consistency, we also build a customer simulation dataset $\mathcal{D}_{sim}$, where the input x includes p and dialogue history h:

$$\mathcal{D}_{sim} = \{(x, y) \mid x = p \oplus h,\ y = u_{cust}\}, \tag{6}$$

where $\oplus$ denotes concatenation and y corresponds to the target customer utterance u_{cust}.

In parallel, the second stream builds the profile-centric retrieval base $\mathcal{M}_{SOP}$ for the SOP Engine. Using extracted profiles p, we organize historical dialogue trajectories to capture persona-specific behavior chains. We use GPT-4o to annotate the SOP stage s_t for each turn, then index dialogue trajectories by profile embeddings via an encoder $\phi(\cdot)$. This repository is formalized as:

$$\mathcal{M}_{SOP} = \{(\phi(p_i), \mathcal{H}_i)\}_{i=1}^{N}, \tag{7}$$

where $\mathcal{H}_i = \{(u_t, r_t, s_t)\}_{t=1}^{T}$ denotes user i's dialogue turns annotated with SOP stages.

3.2 Grouped Simulator Framework

As shown in Figure 3, the Grouped Simulator framework is instantiated in telemarketing scenarios and comprises two distinct subsystems: the **Profile Generation** module, responsible for initializing user profiles, and the **Simulation Core**, which orchestrates dynamic, multi-turn interactions.

3.2.1 Profile Generation

This module initializes the simulation by producing a customer profile.

Profile Model Training. Based on $\mathcal{D}_{gen}$ (Section 3.1), a profile model is SFT-trained to approximate the joint distribution of customer attributes and sample realistic profiles p under constraints. Furthermore, we study the scaling laws of model size and generalization in generating profiles that satisfy complex feature descriptions; details are provided in Appendix A.

Inference and Retrieval. During inference, the module takes customer feature constraints as input, and the profile model generates a textual profile p. To improve behavioral diversity and realism, we apply retrieval augmentation with the vector database $\mathcal{M}_{SOP}$ (Section 3.1). We retrieve the Top-K most similar historical trajectories based on the embedding similarity of profiles:

$$\mathcal{K}_p = \underset{(\phi(p_i), \mathcal{H}_i) \in \mathcal{M}_{SOP}}{\text{Top-K}} (\text{sim}(\phi(p), \phi(p_i))), \tag{8}$$

The output is the generated profile p augmented with retrieved $\mathcal{K}_p$ to ground subsequent simulation.

3.2.2 Simulation Core

The Simulation Core orchestrates multi-turn interaction through a manager-guided loop. Given a customer feature specification x, the Profile Generation module first initializes a customer profile p and retrieves profile-similar historical trajectories $\mathcal{K}_p$ from $\mathcal{M}_{SOP}$. The dialogue history is initialized as $H = \emptyset$. At each turn, the fixed AI-SALESMAN generates the next sales utterance u_{sales} based on H. The Manager then updates the latent customer state based on $(H, p, \mathcal{K}_p)$ and selects dynamic SOP guidance g_{sop}. Finally, the customer model generates $u_{customer}$ conditioned on $\{p, g_{sop}, H\}$, appends it to H, and repeats the loop until the conversation reaches a terminal state.

Group-Aligned Reinforcement Learning. To explicitly capture group homogeneity and mitigate the inherent helpfulness bias of foundation models, we align the customer simulator via the Group Relative Policy Optimization (GRPO) algorithm (Shao et al., 2024), detailed in Appendix C. We design a multi-level reward comprising three components to enforce stylistic, statistical, and semantic consistency, respectively. Specifically, for each training instance $(x, y^*) \in \mathcal{D}_{sim}$, the policy samples a group of candidate responses y conditioned on x, where y^* denotes the logged customer utterance. Inspired by the form–meaning–use view of grammar (Thewlis and Larsen-Freeman, 1993), we design the reward to align generated responses at three complementary levels: surface realization, semantic faithfulness, and group-level behavioral patterns. These levels correspond to the Format, Semantic, and Pattern rewards, respectively, allowing the simulator to preserve the concise style, contextual intent, and cohort-level regularities observed in real telemarketing dialogues.

1. Pattern Reward. We employ a trained discriminator D_ψ (details provided in Appendix B) to assess response matches the real group behavior pattern, utilizing the predicted probability of the generated response y given context c belonging to the real customer distribution as the reward:

$$r_{\text{pattern}}(c, y) = P(\text{label} = \text{Real} \mid c, y; \psi), \quad (9)$$

2. Format Reward. To ensure statistical conformity with the typically concise nature of telemarketing dialogues, we penalize the normalized deviation between the length of the generated response $L(y)$ and the ground truth $L(y^*)$:

$$r_{\text{format}}(y, y^*) = 1 - \left(\frac{|L(y) - L(y^*)|}{L(y^*) + \epsilon} \right)^2, \quad (10)$$

where ϵ is a small smoothing term to prevent division by zero.

3. Semantic Reward. To maintain fidelity to the underlying logic of the reference while allowing for stylistic variation, we compute the cosine similarity between their sentence embeddings $\phi(\cdot)$ with a cutoff threshold δ:

$$r_{\text{sem}}(y, y^*) = \frac{\text{sim}(\phi(y), \phi(y^*)) - \delta}{1 - \delta}. \quad (11)$$

The final GRPO reward is obtained as a weighted combination of the three components:

$$R = \lambda_p r_{\text{pattern}} + \lambda_f r_{\text{format}} + \lambda_s r_{\text{sem}}, \quad (12)$$

with implementation details provided in Appendix E.

The Manager Model. To model non-linear customer decisions, we use a Manager as a hierarchical state controller. It tracks the customer's latent state from dialogue history, retrieves behavior patterns from $\mathcal{M}_{SOP}$, and provides high-level guidance to steer the customer model's generation.

Interaction Workflow. The simulation unfolds as an iterative process: the AI-SALESMAN initiates each turn, prompting the Manager to update the latent state and retrieve the relevant SOP. Subsequently, the AI-CUSTOMER synthesizes the final response $u_{customer}$, conditioned on profile p and the Manager's guidance.

4 Experimental

Dataset Construction. To evaluate the proposed framework within telemarketing contexts, we employ TELESALESCORPUS (Zhang et al., 2025b). This dataset comprises 2000 high-fidelity dialogue sessions spanning diverse business domains. Leveraging the Dual-Stream Data Construction Pipeline detailed in Section 3.1, we process this corpus to construct the training datasets ($\mathcal{D}_{gen}$ and $\mathcal{D}_{sim}$) and the profile-centric retrieval database $\mathcal{M}_{SOP}$.

Model Setup. We benchmark GROUPED SIMULATOR against three representative user simulation paradigms to demonstrate its superior performance in mimicking complex customer behaviors:

Customer Types	Method	Profile Consistency↑			Business Realism↑				Interaction Logic↑			Overall
		Cat.	Pro.	**Avg.**	Bre.	Nat.	Con.	**Avg.**	Int.	Log.	**Avg.**	
Price Sensitive	Prompt-Only	3.15	3.10	3.13	2.55	2.60	2.50	2.55	8.80	8.75	8.78	4.82
	UserLM	7.20	7.15	7.18	4.80	4.85	4.75	4.80	9.30	9.25	9.28	7.09
	USP	7.80	7.75	7.78	6.10	6.05	6.00	6.05	9.15	9.10	9.13	7.65
	Ours	7.85	7.80	**7.83**	7.50	7.45	7.40	**7.45**	9.45	9.40	**9.43**	**8.24**
Resistance Heavy	Prompt-Only	2.80	2.75	2.78	2.20	2.25	2.15	2.20	8.72	8.68	8.70	4.56
	UserLM	7.45	7.40	7.43	4.50	4.55	4.45	4.50	8.95	8.90	8.93	6.95
	USP	7.65	7.60	7.63	5.85	5.80	5.75	5.80	9.18	9.12	9.15	7.53
	Ours	7.70	7.65	**7.68**	7.35	7.30	7.25	**7.30**	9.38	9.32	**9.35**	**8.11**
Status-Quo Oriented	Prompt-Only	3.05	3.00	3.03	2.45	2.50	2.40	2.45	8.83	8.78	8.81	4.76
	UserLM	7.30	7.25	7.28	4.65	4.70	4.60	4.65	9.00	8.95	8.98	6.97
	USP	7.75	7.70	7.73	6.05	6.00	5.95	6.00	9.05	9.00	9.03	7.59
	Ours	7.80	7.75	**7.78**	7.40	7.35	7.30	**7.35**	9.42	9.37	**9.40**	**8.18**
Rational Skeptical	Prompt-Only	2.90	2.85	2.88	2.35	2.40	2.30	2.35	8.76	8.71	8.74	4.66
	UserLM	7.10	7.05	7.08	4.60	4.65	4.55	4.60	8.98	8.93	8.96	6.88
	USP	7.65	7.65	7.65	5.90	5.85	5.80	5.85	9.15	9.10	9.13	7.54
	Ours	7.75	7.70	**7.73**	7.45	7.40	7.35	**7.40**	9.40	9.35	**9.38**	**8.17**
Competition Anxious	Prompt-Only	3.20	3.15	3.18	2.60	2.65	2.55	2.60	8.90	8.85	8.88	4.89
	UserLM	7.25	7.20	7.23	4.90	4.95	4.85	4.90	9.10	9.05	9.08	7.07
	USP	7.85	7.80	7.83	6.20	6.15	6.10	6.15	9.28	9.22	9.25	7.74
	Ours	7.90	7.85	**7.88**	7.60	7.55	7.50	**7.55**	9.50	9.44	**9.47**	**8.30**

Table 1: Performance comparison of GROUPED SIMULATOR versus baseline methods. GROUPED SIMULATOR consistently achieves the strongest results among compared methods, particularly in **Business Realism**, while maintaining competitive profile consistency.

- **Prompt-Only:** Prompting LLMs with designed system instructions to simulate users, without any parameter updates.
- **UserLM (Naous et al., 2025):** A standard SFT paradigm that post-trains on user–assistant dialogues to predict user turns.
- **USP (Wang et al., 2025):** A profile-driven framework that further optimizes the model using RL with cycle consistency rewards.

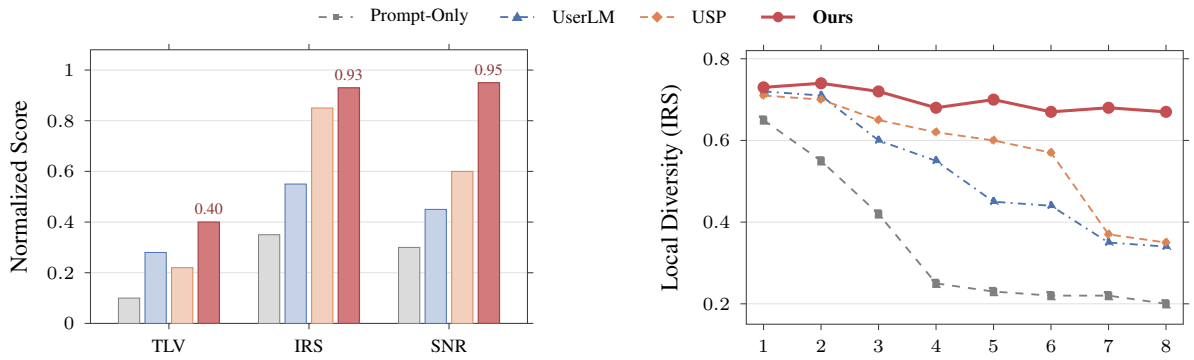
To conduct the multi-turn dialogue evaluation, we use AI-SALESMAN (Zhang et al., 2025b) as the fixed sales agent for all user simulators. For fair comparison, all trainable simulators share the `Qwen2.5-32B-Instruct` backbone, chosen for its best performance–cost tradeoff in AI-SALESMAN. Implementation details are in Appendix E.

4.1 Main Results

Unless otherwise specified, automatic evaluation scores are dialogue-level means. Since training 32B-scale simulators is costly, each trainable method is trained once; we therefore report evaluation-sample means rather than multi-seed means.

Subjective Alignment Assessment. Table 1 shows that GROUPED SIMULATOR consistently outperforms baselines across customer types, with three main findings:

- **Finding 1: Foundation models exhibit robust intrinsic conversational capabilities (S_{IL}).** All methods obtain high interaction-logic scores; even zero-shot Prompt-Only exceeds 8.70 on average. Since our gain on S_{IL} is modest, the main bottleneck lies in behavioral alignment rather than basic fluency.
- **Finding 2: RL effectively enforces Profile Consistency (S_{PC}).** Prompt-Only often fails to satisfy profile constraints, scoring below 3.20, whereas RL-based methods are markedly more stable. USP reaches an average consistency score above 7.60, close to ours, suggesting that explicit RL objectives reduce profile hallucination.
- **Finding 3: Grouped Simulator distinguishes itself through superior Business Realism (S_{BR}).** The largest gap appears in business realism, where baselines often underrepresent real customers' resistance due to helpfulness bias. Our method reaches an



(a) Overall Statistical Comparison

(b) Dynamic Diversity Retention

Figure 4: Multi-dimensional heterogeneity analysis. **(a)** Normalized scores across TLV, IRS, and SNR; the unbounded TLV is proportionalized so that the four methods sum to one, while IRS and SNR are intrinsically bounded. **(b)** Sliding-window analysis of local IRS over dialogue progression (w=3); our method sustains diversity, whereas baselines collapse after the sixth turn.

average realism score of ∼7.45, outperforming USP and UserLM by over 1.4 and 2.6 points, respectively, showing that it suppresses assistant-like behavior in high-friction sales simulation.

Objective Diversity Analysis. We evaluate behavioral heterogeneity using the metrics in Section 2.2.2; for visualization, TLV is normalized to a distribution summing to 1. Figure 4 shows that our model achieves the highest TLV share (0.40), exceeding all baselines, maintains IRS above 0.67 while USP drops from 0.60 to 0.35 after the sixth turn, and reaches 0.95 SNR versus 0.60 for USP. These results indicate that the dual-stream architecture explores diverse SOP states without local-loop trapping.

4.2 Ablation Study

Experimental Setup. To examine each component, we compare GROUPED SIMULATOR with three variants: Prompt-only baseline, Ours w/o Group-Aligned RL, and Ours w/o Dynamic SOP. The two ablated variants are derived by removing one module from Ours, while Prompt-only is a non-trainable baseline. Table 2 reports both subjective alignment and objective diversity.

Effectiveness of Core Modules. The results highlight distinct module roles. Prompt-only retains high interaction logic (8.78) from the base LLM but performs poorly in business realism (2.43), failing to show sales-target resistance. Removing Group-Aligned RL improves profile consistency but yields only moderate business realism (5.05). Removing Dynamic SOP increases realism to 6.95 through stronger RL-induced resistance, but reduces interaction logic (6.30) due to the loss of structured SOP guidance.

Analysis of Synergistic Effects. Combining both modules yields the best overall performance (subjective avg. 8.20; objective avg. 0.76). Group-Aligned RL mitigates helpfulness bias and shapes behavioral tone, while Dynamic SOP preserves coherent dialogue structure, supporting their complementary roles.

Fine-grained Reward Ablation. To isolate reward design, we remove Dynamic SOP and ablate one reward at a time. Table 3 shows that every removal reduces both subjective and objective scores. The Semantic Reward has the largest effect by preserving turn-level relevance, while Pattern and Format further capture cohort-level defensiveness and concise telemarketing rhythm.

4.3 Human Evaluation

To assess the LLM-as-a-Judge protocol, we conduct pairwise human meta-evaluation on 50 dialogue sessions from each of the four systems, yielding 200 outputs. For each dialogue index, we compare all $\binom{4}{2} = 6$ system pairs, with 50 paired comparisons per pair.

Twelve frontline telesales experts participate. Each expert labels one group of 50 comparisons, and each system pair is independently labeled by two experts. Annotators choose system A, tie, or system B under the same three dimensions as the automatic evaluator. We convert LLM scores into the same three-way preferences and compute human–LLM agreement over 600 expert decisions

Method	Subjective Alignment Assessment				Objective Diversity Analysis			
	S_{PC} ↑	S_{BR} ↑	S_{IL} ↑	**Subj. Avg.**	TLV ↑	IRS ↑	SNR ↑	**Obj. Avg.**
Prompt-only baseline	3.00	2.43	8.78	4.74	0.05	0.35	0.30	0.23
Ours w/o Group-Aligned RL	6.92	5.05	7.45	6.47	0.29	0.68	0.82	0.60
Ours w/o Dynamic SOP	7.25	6.95	6.30	6.83	0.27	0.64	0.52	0.48
GROUPED SIMULATOR (Ours)	**7.78**	**7.41**	**9.41**	**8.20**	**0.39**	**0.93**	**0.95**	**0.76**

Table 2: Ablation study results regarding subjective alignment and objective diversity. S_{PC}, S_{BR}, and S_{IL} represent Profile Consistency, Business Realism, and Interaction Logic, respectively.

Reward Setting	Subj. Avg.	Obj. Avg.
All Rewards	6.83	0.48
w/o Format Reward	6.52	0.42
w/o Pattern Reward	6.38	0.39
w/o Semantic Reward	6.15	0.35

Table 3: Compact reward-level ablation within Group-Aligned RL. Dynamic SOP is excluded in all rows to isolate the effect of reward design. Full metrics are provided in Appendix D.

Metric	Human–LLM	Human–Human
Profile Consistency	88.8	88.0
Business Realism	91.0	91.3
Interaction Logic	90.2	92.7

Table 4: Pairwise agreement (%) between expert and LLM-as-a-Judge preferences.

per dimension and human–human agreement over 300 paired annotations.

The agreement rates show that the automatic evaluator largely aligns with expert preferences. Business Realism and Interaction Logic achieve high human–LLM agreement, while Profile Consistency is slightly lower, possibly because persona adherence requires finer-grained interpretation and the compared simulators show smaller differences on this dimension. Human–human agreement remains around 90%, suggesting stable annotations.

5 Related Work

5.1 LLMs-based User Simulator

Advances in LLMs have enabled high-fidelity dialogue simulation. Early LLM-based simulators used prompt-based role-playing (Park et al., 2023; Li et al., 2023; Wang et al., 2024), supporting generalization and social simulation (Park et al., 2022; Horton, 2023). However, RLHF-trained models often exhibit helpfulness bias (Ouyang et al., 2022), becoming over-cooperative or sycophantic (Sharma et al., 2024; Perez et al., 2023). SFT can adapt $p_\theta(y \mid x)$ to domain corpora, but regression-to-the-mean may still yield static personas and limited heterogeneity (Holtzman et al., 2020).

Recent persona-based methods improve controllability and diversity (Takanobu et al., 2020) through explicit profiles (e.g., Character-LLM (Shao et al., 2023), USP (Wang et al., 2025)), but often treat users as static attributes rather than dynamic decision processes. We therefore combine RAG-based trajectory guidance (Lewis et al., 2020) with Group-Aligned RL to retain population-level defensiveness while enabling context-specific heterogeneity.

5.2 User Simulation for Applications

User simulation is widely used in goal-oriented TOD, where performance is measured by task completion and dialogue efficiency (Walker et al., 1997). It also supports RL training and evaluation by reducing the cost of human-in-the-loop interaction (Sekulić et al., 2024; Chang and Chen, 2024).

Recent work extends simulation to proactive strategic tasks such as sales and negotiation (Shea et al., 2024; Gromada et al., 2025; Zhang et al., 2025b), where systems require responsive counterparts for feedback. Because human users are costly to scale, GROUPED SIMULATOR instantiates an AI-Customer as a scalable counterpart for sales-oriented proactive dialogue models in our evaluation.

6 Conclusion

We propose Grouped Simulator, a high-fidelity user simulation framework that balances group homogeneity and individual heterogeneity through Group-Aligned RL and a retrieval-augmented Dynamic SOP engine. By reducing helpfulness bias and static persona failures, GROUPED SIMULATOR supports scalable sales-agent evaluation, while cross-domain validation remains future work.

7 Limitations

Although GROUPED SIMULATOR effectively mitigates LLM helpfulness bias and improves the realism and diversity of user simulations, several limitations remain. Due to the lack of public datasets, experiments are conducted only on TELESALESCORPUS and within the fixed AI-Salesman environment. Therefore, our empirical claims should be interpreted within telemarketing and sales-oriented proactive dialogue rather than as evidence of domain-general user simulation. Moreover, while our automated metrics are efficient, they may not capture all fine-grained subjective aspects; future work could incorporate broader human evaluation or user studies. Finally, this work is intended for pre-deployment evaluation and risk discovery, not for increasing unsolicited telemarketing interactions; any real-world use should follow applicable privacy, consent, and anti-harassment requirements.

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A Scaling Analysis of Profile Generation

In this section, we investigate the impact of model scale on the efficacy of the Profile Generation Module. We conducted Supervised Fine-Tuning (SFT) across four model sizes from the Qwen2.5-Instruct family (7B, 14B, 32B, and 72B) using the same dataset $\mathcal{D}_{gen}$ and hyperparameters.

A.1 Training Dynamics

We first analyze the convergence behavior during training. Figure 5 (Left) depicts the smoothed training loss curves. Consistent with neural scaling laws, we observe a monotonic decrease in training loss as model size increases. The Qwen2.5-72B-Profile model achieves the lowest final loss value (≈ 1.05), significantly outperforming the smaller variants (32B ≈ 1.21, 14B ≈ 1.24, 7B ≈ 1.28). This indicates that larger models can more effectively compress the information contained within the training distribution.

A.2 Generalization and Instruction Following

To evaluate the models' capability to generalize to specific, unseen profile constraints, we designed a *Profile Robustness Test*. We defined five distinct customer archetypes representing challenging sales scenarios: *Resistance-Heavy*, *Price-Sensitive*, *Rational-Skeptical*, *Competition-Anxious*, and *Status-Quo Oriented*.

We generated 100 profiles per model (20 per archetype) and employed GPT-4o as a judge to assess whether the generated text strictly adhered to the profile definition. The evaluation prompt used is shown in Table 5.

A.3 Results and Discussion

The performance results are presented in Figure 5 (Right). While the general trend shows that larger models yield higher pass rates, we observe a notable divergence from the loss curves. Although Qwen2.5-72B-Profile achieved the lowest training loss, Qwen2.5-32B-Profile marginally outperformed it on the generation task (Pass Rate: 94.0% vs. 92.5%).

This finding suggests that for the specific task of profile generation based on structured instructions, the 32B parameter scale may represent a "sweet spot" for generalization efficiency. The lower training loss of the 72B model, combined with slightly inferior generation scores, hints at potential overfitting to the specific lexical patterns of the training data, rather than a deeper grasp of the instruction logic.

LLM-as-a-Judge Prompt

System: You are an expert in analyzing user profiles for sales simulations.
Input: 1. Target Profile Definition: [Insert Definition, e.g., "Resistance-Heavy..."] 2. Generated Profile: [Insert Model Output]
Criteria: Does the Generated Profile explicitly reflect the psychological traits and behavioral patterns described in the Target Profile? - The tone must match. - The specific focus (e.g., ROI, Competitors) must be present.
Output: Return "1" if the profile is valid and accurate, otherwise return "0". Provide a brief reason.

Table 5: The evaluation prompt used for calculating the Pass Rate of generated profiles.

B Details of Pattern Reward Model Construction

To accurately capture the group homogeneity of customer behaviors and quantify the realism of generated responses, we construct a specialized Pattern Reward Model. This model serves as a binary discriminator in our RL pipeline.

B.1 Data Construction

We construct a pairwise comparison dataset $\mathcal{D}_{\text{rm}}$ derived from real-world telemarketing logs.

- **Positive Samples (Real):** We utilize the original customer responses from the dataset as positive instances, representing the ground-truth defensive patterns (e.g., impatience, hang-ups, skepticism).
- **Negative Samples (Synthetic):** To generate hard negative samples that exhibit the helpfulness bias, we employ the untuned

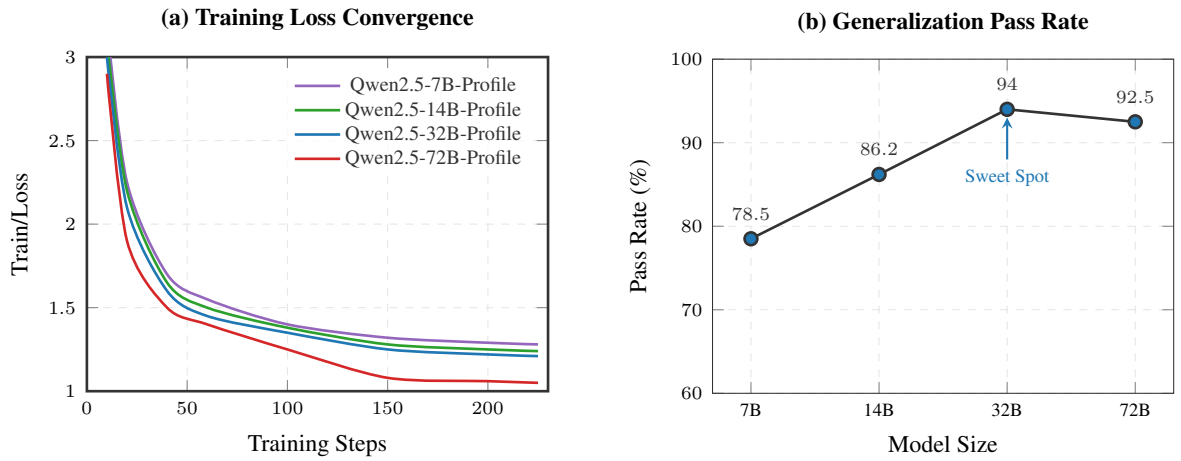

Figure 5: Scaling Analysis. **(a)** Training loss curves for different model sizes. **(b)** Pass rates on the *Profile Robustness Test*. The 32B model exhibits the optimal generalization performance (Sweet Spot), surpassing the 72B model despite having a higher training loss.

`Qwen-2.5-32B-Instruct` model. For each dialogue turn in the training set, we feed the dialogue history into the model and instruct it to role-play as the customer. Although the semantic content is often relevant, these generated responses typically lack the specific defensive tone of real users (often being unnaturally polite or verbose).

This process yields a balanced dataset of pairs (c, y^+, y^-), where c is the context, y^+ is the human response, and y^- is the model generated response.

B.2 Model Training and Evaluation

We employ `Qwen-2.5-7B-Instruct` as the backbone for our reward model due to its efficiency and strong instruction-following capabilities.

Training Setup. We add a linear classification head on top of the last token's hidden state to output a scalar score representing the probability of the input being "Real." The model is fine-tuned using the binary cross-entropy loss:

$$\mathcal{L} = -\mathbb{E}_{(c,y^+,y^-)\sim\mathcal{D}_{\text{rm}}}[\log\sigma(D_\psi(c, y^+)) + \log(1 - \sigma(D_\psi(c, y^-)))]. \quad (13)$$

Performance. We evaluate the discriminator on a held-out test set comprising 10% of the data. The trained reward model achieves a classification accuracy of **82.4%**, demonstrating a robust capability to distinguish between the nuanced linguistic styles of real customers and the generic patterns of LLMs. This high accuracy ensures that the RL signal r_{pattern} effectively guides the policy towards the target *Group Homogeneity*.

C Detailed Formulation of GRPO

This section presents the complete mathematical formulation of Group Relative Policy Optimization (GRPO), which is built upon the Proximal Policy Optimization (PPO) framework. The central idea of GRPO is to estimate advantages by normalizing rewards across a group of parallel rollouts, rather than relying on an explicit value function. This design eliminates the need for training an additional critic network, thereby reducing the overall optimization overhead.

Given a group of G rollouts with scalar rewards $\{R^{(j)}\}_{j=1}^{G}$, GRPO defines the advantage of the i-th sample as the standardized reward within the group:

$$\mathcal{A}^{(i)} = \frac{R^{(i)} - \mathbb{E}_{j\sim U(1,G)}[R^{(j)}]}{\sqrt{\mathbb{V}_{j\sim U(1,G)}[R^{(j)}] + \epsilon}}. \quad (14)$$

Here, $\mathbb{E}[\cdot]$ and $\mathbb{V}[\cdot]$ denote the empirical mean and variance over the G rollouts, and ϵ is a small constant introduced for numerical stability.

Let $q \sim P(Q)$ denote a query sampled from the query distribution, and let $\{o_i\}_{i=1}^{G}$ be the rollouts sampled from the old policy $\pi_{\theta_{\text{old}}}(\cdot \mid q)$. For each rollout $o_i = (o_{i,1}, \ldots, o_{i,|o_i|})$, define the token-level importance ratio as

$$r_{i,t}(\theta) = \frac{\pi_\theta(o_{i,t} \mid q, o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid q, o_{i,<t})}. \quad (15)$$

The GRPO objective then adopts the PPO clipped surrogate objective, combined with a KL-

regularization term:

$$\mathcal{L}_{\text{clip}}(\theta) = \frac{1}{G}\sum_{i=1}^{G}\mathbb{E}_{t\sim o_i}\Big[\min\big(r_{i,t}\mathcal{A}^{(i)}, \\ \text{clip}(r_{i,t}, 1-\epsilon, 1+\epsilon)\mathcal{A}^{(i)}\big)\Big]. \tag{16}$$

$$J_{\text{GRPO}}(\theta) = \mathbb{E}_{q,\{o_i\}}[\mathcal{L}_{\text{clip}}(\theta)] - \beta\, D_{\text{KL}}\big(\pi_\theta \| \pi_{\text{ref}}\big). \tag{17}$$

In this objective, β controls the strength of KL regularization against a reference policy π_{ref}, which stabilizes updates and mitigates overly aggressive policy shifts.

D Detailed Reward-Level Ablation

Table 6 provides the full metric breakdown for the reward-level ablation study discussed in Section 4.2. To isolate the contribution of each reward component, all variants remove the Dynamic SOP engine and differ only in the reward components used by Group-Aligned RL.

E Implementation Details

We provide the comprehensive experimental setups, including training hyperparameters for the Profile Model, User Simulators, and Sales Agent, as well as the inference configurations for evaluation, in Tables 7–10.

For GROUPED SIMULATOR, the Group-Aligned RL reward uses uniform weights for the Pattern, Format, and Semantic rewards, i.e., $\lambda_p = \lambda_f = \lambda_s = 1$. We do not apply additional clipping or normalization to the individual reward components.

For retrieval in the Dynamic SOP engine, we use `gte-Qwen2-1.5B-Instruct` as the profile encoder and retrieve the top $K = 3$ trajectories from the 2,000-entry profile-centric database.

F Evaluation Prompts

We employ GPT-4o as a judge to evaluate the generated dialogues across three distinct dimensions: Persona Consistency, Business Realism, and Interaction Logic. The specific instructions provided to the evaluator are presented in Table 11, Table 12, and Table 13, respectively.

Reward Setting	Subjective Alignment Assessment				Objective Diversity Analysis			
	S_{PC} ↑	S_{BR} ↑	S_{IL} ↑	**Subj. Avg.**	TLV ↑	IRS ↑	SNR ↑	**Obj. Avg.**
All Rewards	7.25	6.95	6.30	6.83	0.27	0.64	0.52	0.48
w/o Format Reward	6.90	6.65	6.01	6.52	0.24	0.58	0.44	0.42
w/o Pattern Reward	6.75	6.50	5.89	6.38	0.21	0.55	0.41	0.39
w/o Semantic Reward	6.45	6.20	5.80	6.15	0.18	0.52	0.35	0.35

Table 6: Full reward-level ablation results within Group-Aligned RL. Dynamic SOP is excluded in all rows to isolate the effect of reward design.

Parameter	7B	14B	32B	72B
Training Configuration (SFT)				
Precision	BF16	BF16	BF16	BF16
Epochs	2	2	2	2
Global Batch Size	256	256	256	256
Learning Rate	2×10^{-5}	2×10^{-5}	2×10^{-5}	2×10^{-5}
Warmup Ratio	0.1	0.1	0.1	0.1
Max Length	2048	2048	2048	2048
DeepSpeed Stage	2	3	3	3
Hardware & Resources				
Num GPUs (80GB)	8	8	32	32
Peak GPU Mem	95%	95%	95%	92%
Training Time (h)	0.5	1	1.5	2

Table 7: Hyperparameters and resource utilization for Profile Model scaling experiments. Consistent with AI-SALESMAN, the 32B model exhibits the optimal trade-off and is selected as the backbone.

Configuration	UserLM	USP	Grouped Simulator (Ours)
Paradigm	SFT	RL (GRPO)	RL (GRPO)
Backbone	Qwen2.5-32B	Qwen2.5-32B	Qwen2.5-32B
Learning Rate	5×10^{-6}	5×10^{-6}	5×10^{-6}
Global Batch Size	256	256	256
Epochs	2	2	2
KL Coefficient	-	0.04	0.04
Max Length	2048	4096	4096
Warmup Ratio	0.1	0.1	0.1
DeepSpeed Stage	3	3	3
Hardware & Resources			
Num GPUs (80GB)	32	32	32
Peak GPU Mem	95%	85%	95%
Training Time (h)	1.5	3	2.5

Table 8: Comparison of training configurations for different user simulators.

Parameter	Value (32B)
Training Configuration (RL)	
Precision	BF16
Epochs	2
Reward Weights	1, 1, 5, 7
Global Batch Size	256
Learning Rate	5×10^{-5}
Warmup Ratio	0.1
DeepSpeed Stage	3

Table 9: Training settings for the fixed AI-SALESMAN agent, adopting the optimal 32B RL configuration from (Zhang et al., 2025b).

Parameter	Profile	User Simulators	AI-Salesman	AI-Manager(GPT-4o)
Model Size	32B	32B	32B	-
Temperature	0.95	0.95	0.95	0.1
Top-p	0.9	0.95	0.9	0.2
Repetition Penalty	1.0	1.05	1.05	1.0
Max New Tokens	512	256	256	1024

Table 10: Inference hyperparameters.

Evaluator: Persona Consistency

You are an expert dialogue system evaluator. Please assess whether the "Customer Simulator" in the following telemarketing scenario remains faithful to its assigned persona category. **[Input Context]**
Customer Profile:
{profile}
Category:
{category}
Dialogue History:
{dialogue_text}
[Evaluation Dimensions (Score 0-10)]

1. **Category Alignment**: Does the customer's reaction align with the psychological traits defined by their category?
   - *Resistance-Heavy*: Shows hostility or attempts to hang up quickly?
   - *Price Sensitive*: Focuses on price, discounts, or hidden costs?
   - *Rational-Skeptical*: Demands data or evidence?
   - *Competition-Anxious*: Mentions competitors or asks for social proof?
   - *Status-Quo Oriented*: Shows inertia, procrastination, or disinterest in changing current workflows?
2. **Profile Adherence**: Does the customer implicitly reflect details from the specific Profile (e.g., shop type, specific pain points) rather than giving generic responses?

[Bias Reduction Guidelines]

- **DO NOT** penalize the customer for a bad attitude, cursing, or refusal to communicate. If the category is "Resistance-Heavy," a rude attitude is a **perfect** score.
- **DO NOT** prefer "cooperative" answers. You are evaluating "resemblance" (how human-like the persona is), not "chat quality."

[Output Format]
Please output strictly in the following JSON format: {{
"reasoning": "<short comment>", "scores": {{ "category_alignment": <int>, "profile_adherence": <int> }}, "weighted_average": <float> }}

Table 11: The evaluation prompt for the **Persona Consistency** dimension. It assesses whether the simulator acts according to its assigned psychological category.

Evaluator: Business Realism

You are a linguistics expert specializing in "Spoken Dialogue" and "Telemarketing Psychology." Please evaluate the realism of the customer's responses in the following conversation. **[Input Context]**
Customer Profile:
{profile}
Category:
{category}
Dialogue History:
{dialogue_text}
[Evaluation Dimensions (Score 0-10)]

1. **Conciseness & Length Penalty**:
   - *High Score*: Sentences are short, fragmented, and concise.
   - *Low Score*: Long-winded, overly logical, or essay-like responses. **Note: telemarketing targets are typically busy. Responses exceeding 3 sentences or 50 words are generally unrealistic and should be heavily penalized.**
2. **Colloquialism**:
   - *High Score*: Uses spoken vocabulary (fillers, slang), inverted sentence structures, or even minor grammatical errors.
   - *Low Score*: Uses textbook-style standard grammar or excessive politeness (e.g., frequent "Sir", "Please").
3. **Context Awareness**:
   - Does the customer appear to be in a busy state? (e.g., "I'm busy right now," "Make it quick").

[Bias Reduction Guidelines]

- This is a **Telemarketing Scenario**. Specifically, it is a transcription of a voice call, NOT a text chat.
- **Strict Penalty for "AI Tone"**: Any response resembling "As a merchant, I think..." or perfectly structured "Firstly, secondly, finally" answers must receive a score of 0-3.
- **Reward Interruptions**: Behaviors such as interrupting the salesperson, inability to hear clearly, or asking to repeat are high-fidelity behaviors and should be rewarded.

[Output Format]
Please output strictly in the following JSON format: {{ "reasoning": "<short comment>", "scores": {{ "brevity_score": <int>, "naturalness_score": <int>, "context_immersion_score": <int> }}, "weighted_average": <float> }}

Table 12: The evaluation prompt for the **Business Realism** dimension. This is the most critical dimension for ensuring the simulator sounds like a real human on a phone call.

Evaluator: Interaction Logic

You are a social psychologist. Please evaluate the interaction logic between the customer and the salesperson in the following dialogue.
[Input Context]
Customer Profile:
{profile}
Category:
{category}
Dialogue History:
{dialogue_text}
[Evaluation Dimensions (Score 0-10)]

1. **Intent Responsiveness**: Did the customer truly understand the salesperson's previous question? (Even if it is a refusal, it should be a targeted refusal rather than gibberish).
2. **Logic Consistency**: Is the change in the customer's attitude natural? (e.g., They should not switch from cursing to extreme enthusiasm in the next turn unless the salesperson provides a compelling benefit).

[Important Note]

- If the salesperson speaks for a long time in the "Dialogue History" and the customer simply replies with "Hmm," "Oh," or "No time," this is **extremely realistic** in telemarketing and should receive a high score for "Logic Consistency."

[Output Format]
Please output strictly in the following JSON format: {{ "reasoning": "<short comment>", "scores": {{ "intent_responsiveness": <int>, "logic_consistency": <int> }}, "weighted_average": <float> }}

Table 13: The evaluation prompt for the **Interaction Logic** dimension. It focuses on the logical flow and responsiveness of the simulator.