

OutboundEval: A Dual-Dimensional Benchmark for Expert-Level Intelligent Outbound Evaluation of Xbench’s Professional-Aligned Series

Pengyu Xu^{1,4*}, Shijia Li^{1,5*}, Ao Sun^{1,6*}, Feng Zhang^{1,8}, Yahan Li^{1,7}, Bo Wu^{1,8}
 Zhanyu Ma¹, Jiguo Li¹, Jun Xu¹, Jiuchong Gao¹, Jinghua Hao¹, Renqing He¹, Rui Wang²
 Yang Liu², Xiaobo Hu², Fan Yang³, Jia Zheng³, Guanghua Yao³

¹ Meituan ² Xbench ³ Agora ⁴ Beijing Jiaotong University ⁵ BUPT

⁶ The Chinese University of Hong Kong, Shenzhen ⁷ Jilin University ⁸ Peking University

Abstract

We propose **OutboundEval**, a comprehensive benchmark for evaluating large language models (LLMs) in expert-level intelligent outbound calling scenarios. Unlike existing methods that suffer from three key limitations—insufficient dataset diversity and category coverage, unrealistic user simulation, and inaccurate evaluation metrics—OutboundEval addresses these issues through a structured framework. First, we design a benchmark spanning six major business domains and 30 representative sub-scenarios, each with scenario-specific process decomposition, weighted scoring, and domain-adaptive metrics. Second, we develop a large-model-driven **User Simulator** that generates diverse, persona-rich virtual users with realistic behaviors, emotional variability, and communication styles, providing a controlled yet authentic testing environment. Third, we introduce a dynamic evaluation method that adapts to task variations, integrating automated and human-in-the-loop assessment to measure task execution accuracy, professional knowledge application, adaptability, and user experience quality. Experiments on 12 state-of-the-art LLMs reveal distinct trade-offs between expert-level task completion and interaction fluency, offering practical insights for building reliable, human-like outbound AI systems. OutboundEval¹ establishes a practical, extensible, and domain-oriented standard for benchmarking LLMs in professional applications.

1 Introduction

With the pervasive integration of Large Language Models (LLMs) across various industries, AI-driven automated outbound calling is emerging as a critical component for enterprises to optimize customer communication and enhance operational efficiency (Wen et al., 2025; Kaewtawee et al., 2025;

Kaiyrbekov et al., 2025; Lang and Eskenazi, 2025). Its applications span a wide range of domains, including recruitment, market research, sales, and customer service, with several benchmarks—such as Xbench (Chen et al., 2025)—having established evaluation criteria for them. However, a standardized benchmark specifically designed for outbound calling scenarios is currently lacking to comprehensively and objectively evaluate the performance of these models in real-world tasks. Existing evaluation efforts predominantly focus on general conversational abilities or single-turn instruction following, and suffer from insufficient dataset volume and category coverage, unrealistic user simulation, and inaccurate or unreasonable evaluation metrics.

To address this gap, we introduce OutboundEval, an evaluation framework designed to drive the advancement of outbound calling AI towards greater intelligence, human-like interaction, and efficiency. This framework assesses the capabilities of outbound calling agents from three primary dimensions: benchmark development, user simulator, and evaluation methodology. Key features of this framework include:

- **Benchmark Development:** We have constructed a comprehensive, scenario-based corpus derived from authentic outbound calling business data. This corpus encompasses six major business domains and 30 representative sub-scenarios. For each sub-scenario, we have established a detailed evaluation scheme that includes scenario-specific process decomposition, a weighted scoring system, and domain-adaptive metrics, forming a solid foundation for nuanced and objective assessment.
- **User Simulator:** To facilitate scalable and consistent evaluation, we propose a systematic process for constructing user simulators. By leveraging interaction data from real-world business scenarios, we build a large number of effective

* Equal Contribution

¹Our paper’s webpage: <https://github.com/LVYUERLVR/OutboundEval-Xbench>

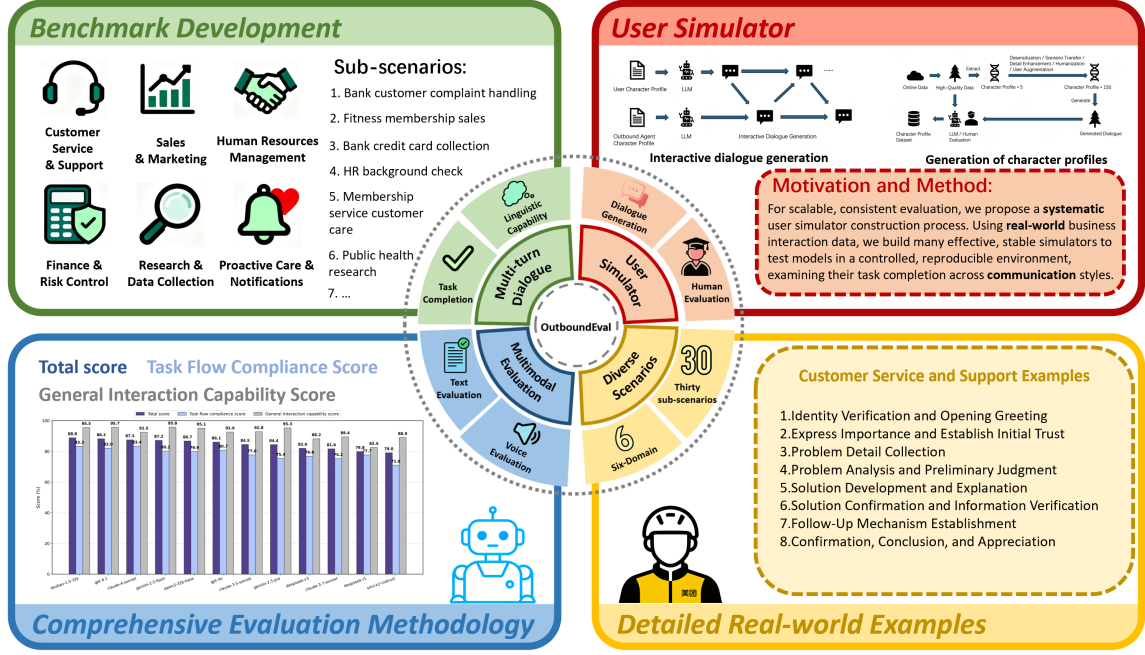


Figure 1: The OutboundEval Framework for Evaluating Outbound Interaction Systems

and stable user simulators. This allows for the testing of models in a controlled and reproducible environment, examining their task completion capabilities across various communication styles.

- **Evaluation Methodology:** In terms of text evaluation, we have developed a dual-layer assessment system comprising task process adherence and general interaction capabilities, achieving precise evaluation through standardized scenario design and quantitative scoring mechanisms. For speech evaluation, we have established 15 metrics across three major scenarios, which integrate expert scoring with objective data to provide multi-dimensional quantification of speech recognition accuracy, system robustness, audio quality, and interactive experience. This comprehensive evaluation framework offers clear technical guidance for optimizing outbound AI systems.

Through this comprehensive design, OutboundEval can thoroughly examine the dialogue generation capabilities and voice interaction quality of AI agents in outbound calling scenarios, offering an objective basis for performance comparison and optimization among different models.

2 Related Work

Evaluation of Task-Oriented Multi-Turn Dialogue

Task-oriented dialogue systems aim to help users accomplish concrete goals such as booking or information lookup, which aligns with outbound calling use cases. Traditional evaluation relies on static, pre-collected corpora and thus cannot faithfully reflect robustness and policy effectiveness under dynamic interaction (Chen et al., 2021; Andreas et al., 2020; Budzianowski et al., 2018). ComplexBench measures instruction following with multi-constraint compositions at scale, but its finely grained constraint combinatorics are not well matched to the behaviors required in dialogue (Wen et al., 2024). This motivates evaluation protocols that capture both global task success and local linguistic competence over multi-turn speech interactions.

This work conducts a comprehensive evaluation of task completion and linguistic capability in outbound calling scenarios, considering both the overall dialogue process and its local segments.

Benchmarks for Speech Language Models

AIR-Bench evaluates SLM understanding of human speech, natural sounds, and music, yet treats audio primarily as contextual input while questions and instructions remain textual (Yang et al., 2024). SD-Eval targets paralinguistic understand-

ing such as emotion, accent, environment, and age, and VoiceBench assesses LLM-based spoken dialogue in realistic scenarios; however, both report only textual outputs and therefore omit evaluation of speech output quality, which is critical in spoken agents (Ao et al., 2024; Chen et al., 2024b). ADU-Bench measures SLM performance on open-domain audio dialogue understanding but does not include multi-turn interaction (Gao et al., 2024). URO-Bench proposes a comprehensive suite for end-to-end spoken dialogue, addressing gaps in multilingual ability, multi-turn interaction, and certain non-linguistic dimensions (Yan et al., 2025). However, it lacks sufficient focus and guidance for practical business scenarios.

This work takes real business scenarios of SLMs as the foundation, integrating text-based evaluation of task completion with speech-based assessment of interaction quality. By doing so, it provides a comprehensive examination of AI agents’ dialogue generation and spoken interaction in outbound calling contexts, offering an objective basis for cross-model comparison and optimization.

User Simulation with Language Models

Language-model-driven simulators have been used to generate interactive agents across settings, including non-player characters in text games (Kim et al., 2022), multi-agent social environments (Wu et al., 2024; Park et al., 2023), and human–AI interaction for online shopping or web search (Chen et al., 2024a; Zhang et al., 2024). τ -bench is the first to deploy LM role simulators for automated agent reliability testing, focusing on retail and airline customer service and demonstrating the feasibility and value of simulation-based evaluation (Yao et al., 2024). Yet prior simulators rarely couple dialogue evaluation with spoken output assessment, and few are grounded in outbound calling workflows.

This work leverages real data from a broader range of business scenarios to construct a large set of simulated human roles. These role simulations create a controllable and reproducible environment for testing agents, enabling systematic evaluation of their performance under different communication styles.

3 Benchmark Development

We implement multi-scenario generalization assessment through a carefully designed domain system

and evaluation strategy.

Six-Domain Scenario System We define six major outbound domains to ensure coverage and representativeness:

1. **Customer Service and Support** — Problem resolution with emotional sensitivity and technical accuracy. These scenarios uniquely require *emotion repair orientation*, where AI must simultaneously resolve issues and transform adversarial customer emotions into collaborative interactions.
2. **Sales and Marketing** — Conversion-oriented persuasion and objection handling. Distinguished by *defense breakthrough orientation*, requiring data-driven value demonstration to overcome customers’ natural skepticism and defensive attitudes toward commercial motives.
3. **Human Resources Management** — Information gathering and candidate matching in a professional yet friendly manner. Characterized by *bidirectional evaluation orientation*, where AI must both assess candidates and be evaluated by them while handling career-sensitive information.
4. **Finance and Risk Control** — High-precision, compliance-sensitive interactions involving sensitive data. Uniquely demands *compliance constraint orientation* with zero-tolerance for errors while balancing strict regulatory requirements with customer experience.
5. **Research and Data Collection** — Structured elicitation of information through guided questioning. Requires *neutrality maintenance orientation*, establishing research authenticity while avoiding any perception of commercial bias.
6. **Proactive Care and Notifications** — Informational outreach with a human touch. Emphasizes *warmth delivery orientation*, prioritizing genuine emotional connection and brand care while addressing concerns about hidden commercial intentions.

OutboundEval encompasses the current mainstream outbound call scenarios. The data is categorized into six major directions. Each major direction contains five sub-scenarios, resulting in a total of 30 sub-scenarios. Furthermore, each sub-scenario includes five different user types, leading to a total of 150 data entries. A detailed description of the data is presented in the table 8 9 10 11 12 13 in Appendix.

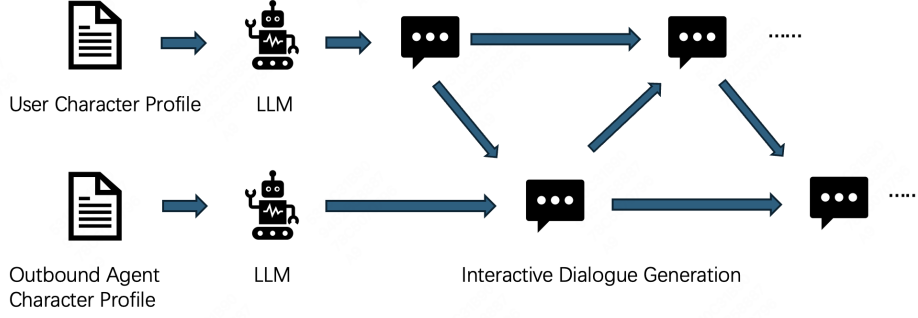


Figure 2: Interactive dialogue generation.

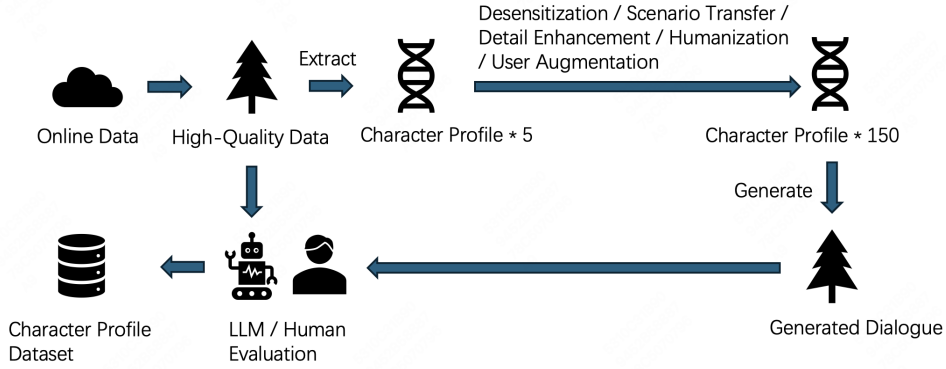


Figure 3: Generation of character profiles.

4 User Simulator

4.1 User Simulator Design

In the domain of automated outbound calling services, evaluating an AI agent’s ability to complete tasks in realistic scenarios is a core yet challenging problem. The primary difficulties arise from the complexity of real-world users, the stochastic nature of communication, and the volatility of human emotions. These factors make it difficult for traditional script-based testing methods to objectively and comprehensively assess the robustness and adaptability of AI agents. To address this bottleneck, we introduce the concept of a **User Simulator**.

Our proposed simulator is a *prompt-based* large language model (LLM), currently implemented using the GPT-4.1 (OpenAI, 2025) architecture (with the potential for iterative upgrades). The simulator plays the role of a diverse set of phone call recipients, engaging with the AI agent under evaluation in dynamic, real-time voice or text interactions. By configuring varied behavioral patterns, knowledge backgrounds, and dialogue strategies, we create a controlled and reproducible experimental environment. This enables systematic evaluation of

the agent’s task completion, adaptability, and communication skills when interacting with different user personalities. Such an approach not only improves evaluation efficiency and scalability but also provides standardized benchmarks for iterative optimization.

4.2 Definition

The User Simulator is a prompt-based LLM. During agent evaluation, we employ two distinct prompt-based LLMs: one as the *User*, and the other as the *Outbound Agent*. The purpose of this interactive setup is to assign each simulated user persona with unique behavior patterns, background knowledge, and conversational strategies, allowing the AI simulator to act as the recipient. This setup ensures that agent performance can be evaluated in a reproducible environment across varying communication styles.

4.3 Construction Pipeline

We design a systematic pipeline comprising data preparation, persona generation, humanization enhancement, and large-scale expansion to construct a high-fidelity user simulator. The pipeline ensures logical coherence and high behavioral realism. The

specific process is shown in Figure 2 and Figure 3.

4.3.1 Structured Persona Definition

Simulator behavior is driven by a structured *persona* document, divided into two parts:

Calling Agent (Outbound Agent):

- **Role:** Definition of the agent’s identity.
- **Core Task:** A concise, single-sentence description of the primary goal.
- **Target Profile:** Basic pre-known information about the user.
- **SOP & Script:** Standard operating procedures and recommended dialogue.
- **FAQ:** Standard responses to common user questions.
- **Opening:** Standardized call introduction.
- **Termination Conditions:** Criteria for successful or failed task completion and corresponding closing statements.

User Simulator (Receiving Party):

- **Role:** Definition of the user’s identity.
- **Background:** Demographics, key experiences, personality traits, and pre-call context.
- **Core Concerns:** Ranked list of primary, secondary, and latent user concerns.
- **Behavioral Patterns:** Descriptions of emotional shifts, uncertainty, and environmental distractions.
- **Style Exemplars:** Positive and negative examples of conversational style to avoid “AI-like” tone.
- **Termination Conditions:** Triggers for ending the call from the user’s side.

4.3.2 Pipeline Steps

Step 1: Seed Data Curation We begin with real-world online conversation data, scoring them on multi-dimensional quality metrics (completeness, logical consistency, informativeness). The top 5 dialogues are selected as seed data for persona modeling.

Step 2: Initial Persona Extraction From the 5 seed samples, we manually craft 5 structured personas following the schema.

Step 3: Scenario Generalization To protect business-sensitive information, personas are recontextualized to generalized outbound domains (e.g., customer service, HR management, finance) using LLM rewriting while preserving information structure and granularity.

Step 4: Data De-identification We systematically replace personal, corporate, and sensitive details using strict substitution rules (e.g., standardized names, placeholder companies, fixed reference dates).

Step 5: Detail Enrichment We enhance SOPs and user backgrounds to improve realism and completeness.

Step 6: Humanization Enhancement We add personality depth via:

- **Persona Enrichment:** Adding situational context affecting dialogue tone.
- **Human Fallibility:** Incorporating emotional variability, memory lapses, biases, and noise.
- **Core Concerns Definition:** Identifying explicit, implicit, and emotional needs.
- **Vernacular Shaping:** Calibrating colloquial style using positive/negative examples.

Step 7: Persona Scaling We expand the 30 finalized personas to 150 using a standardized personality archetype matrix:

1. **Cooperative:** Communicative and positive, with clear needs, friendly demeanor, and prompt decision-making.
2. **Analytical:** Neutral in communication, reliant on information, emotionally calm, and makes decisions after analysis.
3. **Hesitant:** Passive in communication, unclear needs, repeatedly seeks confirmation, and slow in decision-making.
4. **Resistant:** Avoids communication, lacks clear needs, shows impatience, and tends to reject directly.
5. **Efficient:** Goal-oriented with a focus on efficiency; emotionally stable and pursues quick results.

This ensures diversity and coverage across user types.

4.4 Dialogue Generation and Evaluation

Using the 150 persona pairs, we generate simulated dialogues between the User Simulator and the target AI agent.

We adopt three evaluation strategies:

	Score (out of 9)
Human Dialogue	8.50
AI-Generated Dialogue	8.27

Table 1: Score comparison between human and AI-generated dialogues.

Realistic Evaluation	Human	AI
Human Dialogue	150	0
AI Dialogue	149	1

Table 2: Realistic evaluation of human and AI dialogues.

1. **Human-likeness Scoring:** A Turing-test-inspired 0–9 scale based on linguistic naturalness, imperfection, and emotional plausibility.
2. **AI Detection:** Binary classification by an LLM to determine whether a user is AI-generated.
3. **Pairwise Comparison:** Side-by-side judgment of real vs. simulated dialogues.

4.4.1 Human Evaluation

We conduct blind reviews with human annotators:

- **AI Detection:** Classifying each dialogue as human- or AI-generated.
- **Pairwise Comparison:** Identifying which of two dialogues is more likely AI-generated.

Where applicable, statistical hypothesis testing is applied to validate results.

5 Evaluation Methodology

Our evaluation framework comprises two primary components: *text evaluation* and *speech evaluation*. Each task is assessed along two dimensions—**Task Flow Compliance** and **General Interaction Capability**—with weighted aggregation to obtain a comprehensive score.

5.1 Text Evaluation

This section focuses on evaluating the textual aspects of outbound calling performance. The text evaluation protocol in OutboundEval is derived from real-world business scenarios and emphasizes instruction-following performance in goal-oriented, multi-turn dialogues.

Pairwise	Total	Human Win	AI Win
Count	150	64	86
Percentage	100%	42.67%	57.33%

Table 3: Pairwise comparison results between human and AI-generated dialogues.

5.1.1 Evaluation Objectives and Scope

The proposed benchmark is designed to comprehensively assess both the *task execution capabilities* and the *interaction quality* of large language models (LLMs) in realistic outbound business settings. The key objectives are:

1. **Task Execution Capability:** Measure the model’s ability to accomplish predefined business goals within complex, multi-turn dialogues. Unlike single-turn Q&A benchmarks, outbound scenarios require continuous progression of the task flow until the business objective is fulfilled, with emphasis on end-to-end task success and adherence to business processes.
2. **Interaction Experience Capability:** Assess the naturalness and coherence of dialogue, the appropriateness of emotional responses, and robustness in handling incomplete or noisy information. This dimension focuses on fundamental conversational skills that directly impact user perception and satisfaction in outbound calling contexts.
3. **Multi-Scenario Generalization Capability:** Evaluate the model’s ability to maintain consistent performance across diverse outbound business domains. By testing across 6 major business categories and 30 sub-scenarios, this dimension assesses whether the model can generalize effectively to different types of outbound scenarios rather than excelling only in specific domains, thereby measuring the model’s robustness and adaptability in real-world deployment.

5.1.2 Dual-Layer Evaluation Framework

To comprehensively assess both *task execution capabilities* and *interaction experience capabilities*, we design a dual-layer evaluation framework that reflects the dual nature of outbound calling as both a goal-driven task execution process and a user experience-driven communication activity. This framework comprises two primary dimensions: *Task Flow Compliance* (TFC) and *General Interaction Capability* (GIC).

TFC Assessment This dimension evaluates the model’s understanding and execution accuracy of domain-specific business processes through scenario-specific evaluation criteria. Each scenario possesses a unique set of task flow evaluation dimensions derived through systematic workflow decomposition, ensuring that evaluation criteria precisely reflect the specific business requirements and procedural characteristics of each domain.

The evaluation dimension generation process follows a multi-stage pipeline: First, we input the task flow description for each scenario and perform workflow structure analysis, transforming lengthy task flow descriptions into structured workflow node information. Second, these workflow nodes are converted into assessable natural language evaluation criteria through iterative refinement. The process incorporates multiple validation checks, including coverage analysis between derived nodes and original task flows, and overlap detection among different evaluation dimensions. When coverage is insufficient or overlap is excessive, automatic repair mechanisms are triggered to optimize the dimension set. Finally, we establish prerequisite dependencies for each evaluation dimension based on workflow node relationships, enabling assessment of both task execution completion and procedural correctness.

During evaluation, the complete dialogue session serves as the assessment unit. An LLM-based evaluator scores the session against the derived dimension list, determining both task coverage and procedural adherence throughout the conversation.

GIC Assessment This dimension measures fundamental conversational competencies that transcend specific business domains, utilizing eight carefully derived evaluation dimensions that comprehensively capture the essential aspects of professional outbound communication. These dimensions emerge from Meituan’s extensive real-world business experience across diverse outbound scenarios, providing a robust foundation for interaction quality assessment.

The eight evaluation dimensions comprise: *naturalness*, *coherence*, *hallucination handling*, *redundancy*, *emotional richness*, *intent understanding*, *noise resistance*, and *safety issues*. These dimensions comprehensively capture conversational authenticity, logical consistency, factual accuracy, information efficiency, emotional intelligence, user comprehension, robustness, and professional con-

duct respectively.

These dimensions were systematically derived through a bidirectional convergence approach: top-down analysis starting from theoretical model capabilities and progressively refining into specific interaction competencies, and bottom-up synthesis beginning with extensive bad case analysis from real deployment scenarios to identify recurring failure patterns. This dual-perspective methodology ensures comprehensive coverage of both aspirational interaction goals and practical deployment challenges encountered in Meituan’s rich business ecosystem.

The assessment framework employs single-turn response evaluation as the fundamental scoring unit. This granular approach addresses the inherent limitations of LLM-based evaluation systems, where scoring multiple aspects simultaneously can lead to capability dilution and reduced assessment accuracy. By focusing evaluation attention on individual responses, we enhance scoring precision and enable more reliable capability measurement across the eight dimensions. The detailed scoring criteria and evaluation rubrics for each dimension are provided in the appendix.

Cross-Domain Evaluation Strategy These distinct orientations ensure that models must demonstrate fundamentally different capabilities across scenarios. Each domain features 5 sub-scenarios with 5 user personality types, creating 150 evaluation instances for comprehensive assessment.

5.1.3 Scoring and Weighting Design

To ensure comprehensive and accurate assessment, we design a systematic scoring framework that integrates both evaluation dimensions through carefully calibrated weighting schemes.

Score Components Definition Our evaluation framework generates three types of scores:

Coverage Score (Cov) combines two sub-components: *Key Node Completion Rate* evaluates performance on critical workflow checkpoints that determine task success or failure; *Overall Node Completion Rate* provides comprehensive assessment across the complete evaluation checklist, including branch nodes for exceptional scenarios.

Process Score (Proc) examines the correctness of task execution sequence, ensuring proper business logic adherence and preventing procedural violations.

GIC Score aggregates eight conversational competency dimensions with specific weights, measuring fundamental interaction capabilities that transcend business domains.

Scoring Formulas and Weight Allocation All weight assignments result from extensive empirical validation through systematic experiments comparing automated scoring consistency with human expert evaluations.

TFC Score Calculation:

$$\text{TFC} = 0.70 \text{ Cov} + 0.30 \text{ Proc.}$$

Final Score Calculation:

$$\text{Final} = 0.55 \text{ TFC} + 0.45 \text{ GIC.}$$

The Cov weighting (0.7 for key nodes, 0.3 for overall nodes) reflects the fundamental principle that successful task completion depends primarily on executing critical business steps, while comprehensive coverage provides additional robustness assessment. Furthermore, the TFC weighting (0.7 for Cov, 0.3 for Proc) prioritizes task completion degree over procedural correctness, recognizing that in outbound calling scenarios, achieving the business objective is more critical than strict adherence to execution order. Both weight allocations emerged from extensive empirical validation studies, with the 7:3 ratios demonstrating that key node performance and task coverage serve as the strongest predictors of real-world task success, while procedural adherence and overall coverage contribute valuable supplementary insights for service quality optimization.

For GIC, the eight-dimension weighting scheme prioritizes three foundational conversational competencies—**naturalness**, **coherence**, and **hallucination handling**—each weighted at 20%, collectively accounting for 60% of the GIC score. This reflects their critical importance in professional outbound communication. The remaining five dimensions are weighted according to their frequency of impact and business criticality in real deployment scenarios, as detailed in Table 5.

5.1.4 Benchmark Results

We conducted a comprehensive evaluation of 12 state-of-the-art large language models (LLMs) under the proposed framework. The results (Table 6) show that **doubao-1.5-32k** (BytetDance, 2025) ranked first with an overall score of 0.8881,

demonstrating strong capabilities in both TFC (0.8331) and GIC (0.9554). In contrast, **kimi-k2-instruct** (Kimi-Team et al., 2025) ranked last due to its relatively low TFC score (0.7095), indicating that despite achieving reasonable conversational fluency, it exhibits significant deficiencies in task-oriented competencies such as complex instruction comprehension and procedural adherence.

The evaluation results further reveal several key insights:

First, model parameter count is not the sole determinant of performance. For instance, the relatively smaller **Gemini-2.5-Flash** (Comanici et al., 2025) slightly outperformed its larger counterpart, **Gemini-2.5-Pro** (Comanici et al., 2025), in GIC; while **claude-4-sonnet** (Anthropic, 2025b) achieved the highest TFC score (0.8339) yet ranked only third overall due to its gap in GIC. This indicates that for specific scenarios, factors such as model architecture, training data quality, and alignment optimization strategies (e.g., RLHF) may be more critical than model scale alone.

Second, the performance of leading models shows clear stratification. The top eight models all achieved overall scores above 0.84, forming a high-performance cluster, which indicates that LLMs have reached a substantial baseline capability in outbound dialogue scenarios. However, the gap between the top-performing model and the theoretical maximum score reveals that existing technologies still face challenges in handling highly complex, multi-turn, or uncertain real-world conversations.

Third, the trade-off between TFC and GIC across models provides important insights for model selection in practical applications. For example, the “high TFC but relatively lower GIC performance” pattern (such as Claude-4-Sonnet) makes them highly suitable for standardized tasks with strict processes and low error tolerance (e.g., information verification, appointment scheduling). Conversely, models with balanced performance across both dimensions are better suited for customer service and communication scenarios that require high emotional intelligence and the ability to sustain multi-topic conversations.

In summary, current large language models have established a solid foundation for outbound scenarios, but the performance variations reflect trade-offs and different emphases among technical approaches. Future work may explore directions such as integrating the strengths of different models, de-

Main Dimension	Sub Dimension	Weight
Coverage Score	Key Node Completion Rate	0.7
	Overall Node Completion Rate	0.3
Process Score	Execution Order Score	1

Table 4: Dimension and Weight Distribution

Dimension	Weight
Naturalness	0.20
Coherence	0.20
Hallucination Handling	0.20
Redundancy	0.10
Emotional Richness	0.10
Intent Understanding	0.10
Noise Resistance	0.06
Safety Issues	0.04

Table 5: GIC Evaluation Dimensions and Weights

veloping more advanced alignment algorithms, and constructing more complex test scenarios.

5.1.5 Human Verification

While LLMs automatically decompose task flows and generate evaluation points, human verification by domain experts plays a critical role in ensuring framework reliability. Our human-in-the-loop validation operates across three key stages:

TFC Dimension Validation After LLM-based workflow decomposition, domain experts conduct comprehensive reviews focusing on dimension coverage and prerequisite dependency allocation. Human validators examine whether the derived evaluation dimensions comprehensively capture all critical business steps and verify the logical sequencing of evaluation points. Through systematic validation, we achieved over **95% consistency** between automated decomposition and expert judgment. For cases where discrepancies occurred, human experts manually refined the dimension sets to ensure both completeness and business logic adherence, thereby establishing the rationality and comprehensiveness of our TFC evaluation framework.

GIC Evaluation Consistency For the General Interaction Capability assessment, we established systematic consistency validation between LLM-based evaluation and human expert scoring. Through iterative refinement of evaluation prompts based on

human feedback, we achieved **90% consistency** between automated and manual assessments. Cases with lower consistency triggered prompt optimization cycles, where human experts provided detailed feedback to enhance evaluation accuracy and reliability.

Scoring Framework Calibration To validate our dual-dimensional scoring approach, we conducted extensive comparative experiments between automated evaluation and human expert assessment. Multiple rounds of iterative validation across diverse scenarios enabled us to calibrate the weighting schemes and scoring formulas. This rigorous validation process confirmed the effectiveness of our current framework design, ensuring that automated scores align closely with expert professional judgment.

This comprehensive human verification process ensures that our evaluation framework maintains high accuracy, domain relevance, and practical applicability across diverse outbound calling scenarios.

5.2 Voice Evaluation

5.2.1 Evaluation Objectives

This section focuses on evaluating the speech interaction quality in outbound calling scenarios. The speech evaluation protocol in OutboundEval is derived from real-world business scenarios and emphasizes the quantification of speech output naturalness, clarity, and user experience in goal-oriented, multi-turn dialogues.

5.2.2 Metric Definition

The intelligent customer service dialogue evaluation framework is structured around three core components: at the multi-turn dialogue level, it focuses on usability to ensure accurate processing of speech input, emphasizes interruption experience for timely detection and response to user interruptions, and aims for low response latency to minimize waiting; in speech recognition, it prioritizes transcription accuracy as the foundation for under-

Rank	Model Name	Total Score	Task Flow Compliance Score	General Interaction Capability Score
1	doubao-1.5-32k (BytetDance, 2025)	0.8881	0.8331	0.9554
2	gpt-4.1 (OpenAI, 2025)	0.8818	0.8204	0.9568
3	claude-4-sonnet (Anthropic, 2025b)	0.8748	0.8339	0.9248
4	gemini-2.5-flash (Comanici et al., 2025)	0.8719	0.8016	0.9578
5	qwen3-32b-base (Yang et al., 2025)	0.8672	0.7986	0.9510
6	gpt-4o (OpenAI, 2024)	0.8606	0.8072	0.9258
7	claude-3.5-sonnet (Anthropic, 2024)	0.8448	0.7764	0.9283
8	gemini-2.5-pro (Comanici et al., 2025)	0.8438	0.7544	0.9530
9	deepseek-v3 (DeepSeek-AI et al., 2025b)	0.8195	0.7683	0.8821
10	claude-3.7-sonnet (Anthropic, 2025a)	0.8162	0.7522	0.8944
11	deepseek-r1 (DeepSeek-AI et al., 2025a)	0.7984	0.7767	0.8250
12	kimi-k2-instruct (Kimi-Team et al., 2025)	0.7904	0.7095	0.8894

Table 6: Ranking of models by total score, task flow compliance score, and general interaction capability score.

standing and enhances robustness against accents and noisy environments; for speech synthesis, it demands high audio clarity and naturalness while pursuing fluid and authentic interactive experiences.

A detailed description is presented in the table 19 20 in Appendix.

6 Conclusion

In this work, we presented **OutboundEval**, a comprehensive evaluation framework for large language model-based outbound calling agents. Our work primarily contributes the following innovations: First, a real-world business data-driven evaluation framework and user simulator design; Second, a standardized pipeline with generalizable User Simulator Prompt. By integrating text-based and speech-based assessments with realistic role-simulated interactions, our approach enables fine-grained analysis of both task flow compliance and conversational quality. Experimental results demonstrate the framework’s effectiveness in capturing key aspects of real-world outbound scenarios, providing valuable insights for both academic research and industrial deployment.

7 Limitations

While OutboundEval offers a standardized and reproducible evaluation protocol, it has several limitations. First, the current role simulation is primarily prompt-based and may not fully capture the diversity and unpredictability of real human behavior. Second, the framework focuses on pre-defined out-

bound scenarios, which may limit generalization to novel domains. Finally, real-time factors such as network latency, speech synthesis artifacts, and ASR errors are only partially modeled, suggesting future work should incorporate more realistic end-to-end conditions.

Acknowledgment

We thank all collaborators and domain experts for their valuable feedback during the design and evaluation of OutboundEval. This work was supported in part by industry partners in the customer service and AI research communities, whose practical insights greatly enhanced the realism and applicability of the proposed framework.

References

- Jacob Andreas, John Bufe, David Burkett, Charles Chen, Josh Clausman, Jean Crawford, Kate Crim, Jordan DeLoach, Leah Dorner, Jason Eisner, et al. 2020. Task-oriented dialogue as dataflow synthesis. *Transactions of the Association for Computational Linguistics*, 8:556–571.
- Anthropic. 2024. [Claude 3.5 sonnet](#).
- Anthropic. 2025a. [Claude 3.7 sonnet and claude code](#).
- Anthropic. 2025b. [Introducing claude 4](#).
- Junyi Ao, Yuancheng Wang, Xiaohai Tian, Dekun Chen, Jun Zhang, Lu Lu, Yuxuan Wang, Haizhou Li, and Zhizheng Wu. 2024. Sd-eval: A benchmark dataset for spoken dialogue understanding beyond words. *Advances in Neural Information Processing Systems*, 37:56898–56918.

- Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. Multiwoz—a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling. *arXiv preprint arXiv:1810.00278*.
- BytetDance. 2025. [Doubao-1.5-pro](#).
- Derek Chen, Howard Chen, Yi Yang, Alex Lin, and Zhou Yu. 2021. Action-based conversations dataset: A corpus for building more in-depth task-oriented dialogue systems. *arXiv preprint arXiv:2104.00783*.
- Kaiyuan Chen, Yixin Ren, Yang Liu, Xiaobo Hu, Haotong Tian, Tianbao Xie, Fangfu Liu, Haoye Zhang, Hongzhang Liu, Yuan Gong, et al. 2025. xbench: Tracking agents productivity scaling with profession-aligned real-world evaluations. *arXiv preprint arXiv:2506.13651*.
- Sanxing Chen, Sam Wiseman, and Bhuwan Dhingra. 2024a. Chatshop: Interactive information seeking with language agents. *arXiv preprint arXiv:2404.09911*.
- Yiming Chen, Xianghu Yue, Chen Zhang, Xiaoxue Gao, Robby T Tan, and Haizhou Li. 2024b. Voicebench: Benchmarking llm-based voice assistants. *arXiv preprint arXiv:2410.17196*.
- Gheorghe Comanici, Eric Bieber, Mike Schaekermann, Ice Pasupat, Noveen Sachdeva, Inderjit Dhillon, Marcel Blistein, Ori Ram, Dan Zhang, Evan Rosen, Luke Marris, Sam Petulla, Colin Gaffney, Asaf Aharoni, Nathan, et al. 2025. [Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities](#).
- DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, et al. 2025a. [Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning](#).
- DeepSeek-AI, Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Daya Guo, Dejian Yang, Deli Chen, Dongjie Ji, Erhang Li, et al. 2025b. [Deepseek-v3 technical report](#).
- Kuofeng Gao, Shu-Tao Xia, Ke Xu, Philip Torr, and Jindong Gu. 2024. Benchmarking open-ended audio dialogue understanding for large audio-language models. *arXiv preprint arXiv:2412.05167*.
- Krittanon Kaewtawee, Wachiravit Modetruea, Krittan Pachtrachai, and Touchapon Kraisingkorn. 2025. [Cloning a conversational voice ai agent from call recording datasets for telesales](#).
- Kurmanbek Kaiyrbekov, Nicholas J Dobbins, and Sean D Mooney. 2025. Automated survey collection with llm-based conversational agents. *arXiv preprint arXiv:2504.02891*.
- Minsoo Kim, Yeonjoon Jung, Dohyeon Lee, and Seungwon Hwang. 2022. Plm-based world models for text-based games. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 1324–1341.
- Kimi-Team, Yifan Bai, Yiping Bao, Guanduo Chen, Jiahao Chen, Ningxin Chen, Ruijue Chen, Yanru Chen, Yuankun Chen, Yutian Chen, Zhuofu Chen, Jialei Cui, Hao Ding, Mengnan Dong, Angang Du, Chenzhuang Du, et al. 2025. [Kimi k2: Open agentic intelligence](#).
- Max M Lang and Sol Eskenazi. 2025. Telephone surveys meet conversational ai: Evaluating a llm-based telephone survey system at scale. *arXiv preprint arXiv:2502.20140*.
- OpenAI. 2024. [Hello gpt-4o](#).
- OpenAI. 2025. [Introducing gpt-4.1 in the api](#).
- Joon Sung Park, Joseph O’Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th annual acm symposium on user interface software and technology*, pages 1–22.
- Bo Wen, Chen Wang, Qiwei Han, Raquel Norel, Julia Liu, Thaddeus Stappenbeck, and Jeffrey L Rogers. 2025. Voice-based ai agents: Filling the economic gaps in digital health delivery. In *2025 IEEE International Conference on Digital Health (ICDH)*, pages 220–232. IEEE.
- Bosi Wen, Pei Ke, Xiaotao Gu, Lindong Wu, Hao Huang, Jinfeng Zhou, Wenchuang Li, Binxin Hu, Wendy Gao, Jiaying Xu, et al. 2024. Benchmarking complex instruction-following with multiple constraints composition. *Advances in Neural Information Processing Systems*, 37:137610–137645.
- Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, et al. 2024. Autogen: Enabling next-gen llm applications via multi-agent conversations. In *First Conference on Language Modeling*.
- Ruiqi Yan, Xiquan Li, Wenxi Chen, Zhikang Niu, Chen Yang, Ziyang Ma, Kai Yu, and Xie Chen. 2025. Uro-bench: A comprehensive benchmark for end-to-end spoken dialogue models. *arXiv preprint arXiv:2502.17810*.
- An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, Chuji Zheng, Dayiheng Liu, Fan Zhou, Fei Huang, Feng Hu, Hao Ge, Haoran Wei, et al. 2025. [Qwen3 technical report](#).
- Qian Yang, Jin Xu, Wenrui Liu, Yunfei Chu, Ziyue Jiang, Xiaohuan Zhou, Yichong Leng, Yuanjun

Ly, Zhou Zhao, Chang Zhou, et al. 2024. Air-bench: Benchmarking large audio-language models via generative comprehension. *arXiv preprint arXiv:2402.07729*.

Shunyu Yao, Noah Shinn, Pedram Razavi, and Karthik Narasimhan. 2024. τ -bench: A benchmark for tool-agent-user interaction in real-world domains. *arXiv preprint arXiv:2406.12045*.

Erhan Zhang, Xingzhu Wang, Peiyuan Gong, Yankai Lin, and Jiaxin Mao. 2024. Usimagent: Large language models for simulating search users. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2687–2692.

Appendix

Step	Data	Description	Operation
1	Online Data	Real online data	–
2	Seed Data	5 pieces of high-quality real online data	Score the online data based on conversation quality to obtain 5 high-quality samples as seed data.
3	Role Setting Data	5 role settings for call initiators/recipients	Extract structured role settings from the seed data.
4	Desensitized Data	30 role settings for various scenarios	Perform scenario migration and desensitization; generalize and synthesize data for more scenarios based on seed data.
5	Re-desensitized Data	30 desensitized role settings	Replace placeholders and remove private/sensitive information.
6	Detail-Enhanced Data	30 role settings with enriched details	Add more details, especially step-by-step processes and core concerns.
7	Anthropomorphic Data	30 role settings with enhanced anthropomorphism	Increase human-likeness to make it hard to distinguish from real people.
8	Expanded Data	150 expanded role settings	Expand personas based on different user types.
9	Evaluation (Auto)	Automatically evaluate conversation generation quality	Use LLM-as-Judger to assess generated conversation quality.
10	Evaluation (Manual)	Manually blind-evaluate conversation generation quality	Conduct human blind evaluation to test if people can distinguish generated conversations from real ones.

Table 7: Data processing pipeline for user simulator construction.

Sub-scenario	Core Objective	Main Challenges
Bank customer complaint handling	Address abnormal account deductions, clarify deduction reasons, provide solutions, and restore customer trust.	Customers are dissatisfied with the bank's efficiency and lack of trust; requires building confidence within a short time while keeping promises.
E-commerce platform return/exchange processing	Assist customers in completing the return/exchange process to improve satisfaction levels.	Customers may have doubts about new service models; tight time constraints add pressure.
Enterprise technical support sales	Promote enterprise-level system optimization services to customers, resolve existing technical issues, and facilitate service upgrades.	Lack of trust in service providers; high budget pressures; concerns over migration risks for systems.
Home appliance repair service scheduling	Confirm fault conditions for customers who have submitted repair requests and successfully arrange on-site repair appointments.	Customers are sensitive to costs and worry about being overcharged; requires communication in a quiet office environment with low-pressure tone.
Telecom customer satisfaction follow-up survey	Collect customer feedback regarding recent network issues, evaluate satisfaction levels, and gather suggestions for improvement.	Customers are dissatisfied with network stability; tight timelines require quick issue resolution.

Table 8: Sub-scenario,Core Objective and Main Challenges in Customer Service and Support

Sub-scenario	Core Objective	Main Challenges
Fitness Membership Sales	Promote fitness memberships and encourage customers to visit the gym for an experience.	Customers are price-sensitive and worry about not being able to persist due to heavy commitments.
Cloud Service Sales	Recommend cloud service solutions to small and medium-sized manufacturing enterprises, improving their digitalization efficiency.	Customers lack trust in IT products, worrying about system complexity and data security issues.
B2B Enterprise Procurement System Promotion	Attract new registered enterprise users, activate them, and guide them through core functionalities of the system to increase user engagement levels.	Customers doubt the reliability of the new platform; concerns over complex operations affecting procurement efficiency exist.
Online Education Renewal Services	Encourage existing customers to renew subscriptions while increasing customer retention rates.	Customers have budget constraints and feel they lack time for continued learning after renewal fees are paid.
Software Product Sales	Introduce intelligent office systems tailored for small- and medium-sized manufacturing enterprises, encouraging trials or purchase intent generation.	Customers harbor skepticism towards software products with a defensive mindset; they require concrete data evidence proving product value before trusting it fully.

Table 9: Sub-scenario,Core Objective and Main Challenges in Sales and Marketing

Sub-scenario	Core Objective	Main Challenges
Corporate Recruit- ment Outreach	Proactively contact job seekers for initial communication, introduce job positions and company details, and guide candidates through the interview process.	Candidates find it inconvenient to en- gage deeply in office environments; they need limited-time opportunities to establish interest in the position.
HR Background Check	Emphasize verifying the authenticity of work experience, responsibilities within roles, performance at work, and reasons for leaving previous jobs.	Concerns about legal compliance during background checks arise; sen- sitive information like salary may cause discomfort or limited willing- ness to cooperate due to time con- straints.
Interview Schedul- ing for Recruitment	Coordinate with shortlisted candidates on confirming interview times and formats to complete scheduling agreements effi- ciently.	Candidates who are currently em- ployed face challenges adjusting their schedules; uncertainty exists regarding interview timing arrange- ments.
HR Onboarding Pro- cess Assistance	Assist new employees in completing on- boarding tasks smoothly while ensuring proper handling of necessary formalities such as benefits processing.	New hires may feel apprehensive about adapting to a new environ- ment; detailed explanations of pro- cesses can alleviate concerns over timelines and procedures.
Internal Employee Training Promotion	Encourage employees to participate in in- ternal technical training courses aimed at improving engagement levels among staff members.	Employees doubt the quality of train- ing and feel their busy work sched- ules create time constraints, limiting participation.

Table 10: Sub-scenario,Core Objective and Main Challenges in Human Resource Management

Sub-scenario	Core Objective	Main Challenges
Bank Credit Card Collection	Assist overdue customers in creating repayment plans to promote debt recovery.	Customers face difficulties in repaying due to decreased income and need a balance between collection effectiveness and actual affordability.
Bank Loan Business Follow-up Verification	Verify the authenticity of customer credit loan application information and facilitate the approval process.	Customers urgently need funds but have unstable incomes, leading to concerns about approval timeframes and high expectations for quick processing.
Bank Account Security Risk Control Services	Alert customers about abnormal transaction risks on their accounts and guide them toward adopting security measures.	Customers are highly skeptical of electronic identity verification processes; they feel unable to immediately cooperate due to work-related constraints or doubts regarding safety protocols.
Bank Loan Collection	Collaborate with overdue customers on feasible installment repayment plans, reducing losses while mitigating bank risk exposure.	Significant drops in income reduce repayment ability; skepticism exists around installment terms as well as potential impacts on credit scores.
Financial Management Product Renewal Services	Encourage customers to renew or upgrade financial products upon maturity.	Customers prioritize liquidity needs over long-term benefits, as their risk tolerance and affordability are limited; they often prefer flexible cash flow options.

Table 11: Sub-scenario,Core Objective and Main Challenges in Finance and Risk Control

Sub-scenario	Core Objective	Main Challenges
Public Health Research	Collect data on community residents' health habits, disease prevention awareness, and healthcare service needs.	Customers doubt the authenticity of phone-based identity verification; tight schedules demand quick completion and limit understanding of professional health knowledge.
Bank Customer Information Maintenance Services	Verify and update basic customer information for banking purposes.	Customers question the legitimacy of phone inquiries and worry about fraud risks during communication processes.
Smart Home Product User Experience Research	Gather user feedback on smart home product usage to improve functionality based on suggestions.	Users have limited time due to commuting or other constraints; they require comprehensive information collection within a short timeframe.
Smart Home Market Research	Collect data on target users' preferences, usage patterns, and purchase intentions for smart home products.	Customers doubt the authenticity of research inquiries; tight schedules require quick establishment of trust and efficient information collection.
Brand Awareness Market Research	Gather consumer insights on brand recognition, user experience, purchasing preferences, and suggestions for improvement.	Consumers may exhibit defensive attitudes toward unfamiliar calls; they need proof of research authenticity and prefer timely completion of data collection to avoid disruptions.

Table 12: Sub-scenario,Core Objective and Main Challenges in Research and Information Collection

Sub-scenario	Core Objective	Main Challenges
Hospital Surgery Appointment Confirmation	Confirm surgery appointment times and inform patients about pre-surgery preparation details.	Patients may face scheduling conflicts and have concerns regarding the safety of surgical procedures.
Enterprise Logistics Services and Value-added Service Sales	Notify customers of important delivery updates while promoting VIP value-added services to enhance customer loyalty.	Customers are cautious about promotional services, showing a defensive mindset with attention to cost control.
Membership Service Customer Care	Remind members of upcoming expiration dates while encouraging renewal or points redemption.	Customers lack understanding of membership benefits and point usage; tight schedules discourage complex operations for renewals or redemptions.
Banking System Maintenance Notification	Notify customers in advance about system maintenance schedules to ensure they understand potential service interruptions and alternative solutions.	Customers with prior negative experiences regarding system maintenance are sensitive; they require detailed explanations and assurance of data security.
Lifestyle Service Platform Customer Care	Send birthday greetings or other personalized messages to maintain customer relationships and enhance brand loyalty.	Customers with busy work schedules may have limited time for engagement, while unsolicited calls may raise concerns about commercial intent.

Table 13: Sub-scenario,Core Objective and Main Challenges in Proactive Care Notifications

Indicator Type	Indicator	Definition
Usability	Selective Attention Success Rate (SASR) Under the interference of noise, the efficiency of the attention mechanism in focusing on key information. It is similar to how a person shields external interference and can always focus on critical tasks.	- Number of dialogues for successfully perceiving the dialogue partner's task / Total number of dialogues * 100% - Definition of success perception: Accurately capture the dialogue partner and correctly perceive the intention of the dialogue partner
Experience	500ms Interruption Success Rate (ISR) Refer to the 500ms. Generally speaking, if the delay exceeds 500ms, people will have an obvious perception.	- When AI is speaking, if the continuous voice of the dialogue partner is detected and recognized as a voice interruption signal, it is recorded as a successful interruption - When testing two Agents, how to construct the problem of whether to interrupt - Interruption delay = Time when AI stops speaking - Time of the first word of the dialogue partner's interruption - If the interruption delay < 500ms, it is recorded as the number of successful 500ms interruptions - 500ms Interruption Success Rate = Number of successful 500ms interruptions / Total number of successful interruptions
	End - to - End Responding Latency Response latency is an important experience indicator, similar to how fast a person's reaction speed is. However, at present, there is no cognition of the latency threshold. The existing cognition is from luxury to frugality. It is similar to the refresh rate of a mobile phone screen. After experiencing a high - refresh screen, it is difficult to accept the experience of an ordinary screen.	- End - to - End Responding Latency = Time of the first word of AI's response - Time of the last word of the dialogue partner's speech

Table 14: Indicator Definition Table

Dimension	Indicator	Definition	Calculation Logic
Accuracy	WER (Word Error Rate)	Proportion of word-level errors (substitution + insertion + deletion) relative to the total number of words	$\frac{S+I+D}{N_{\text{ref}}} \times 100\%$
	CER (Character Error Rate)	Character-level error rate (suitable for Chinese/Japanese, etc.)	Same as WER, computed at the character level
	Proper Noun Accuracy	Recognition accuracy of key information such as names, places, and domain terms	Count correct recognition over target entities
Robustness	Accent Adaptability	Degradation in recognition accuracy for dialects or non-native accents	Relative WER/CER change vs. standard accent
	WER in Noisy Environment	Recognition error rate when the signal-to-noise ratio is < 15 dB (e.g., in-vehicle or factory scenarios)	Compute WER under controlled SNR conditions
	Rejection Rate	Proportion of correctly returning “don’t understand” for unrecognizable input (to avoid forced wrong output)	Correct rejections / (correct rejections + false accepts)

Table 15: Indicator table for ASR accuracy and robustness.

Dimension	Indicator	Definition	Measurement Tool
Sound Quality	MOS (Mean Opinion Score)	Subjective sound quality rating (1-5 points, requires multiple people to test)	ITU-T P.800 Standard
	Naturalness NISQA	Objective speech naturalness rating (based on deep learning model)	NISQA Open-Source Tool
	Symbol Mispronunciation Rate	Proportion of mispronounced numbers/letters/special symbols (e.g., #, @)	Automated Symbol Test Set
Interaction Experience	Emotional Matching Degree	Consistency between speech emotion (e.g., happy/serious) and text semantics	
	Multilingual Switching Fluency	Pronunciation naturalness in mixed Chinese-English scenarios (e.g., "USB" pronounced as "U-S-B Interface")	
	Speech Rate Adaptation	Automatically adjust speech rate based on content importance (e.g., slow down for key information)	

Table 16: Speech-Related Indicators and Their Descriptions

Dimension	Element	Description and Example
Basic Information	Belonging Scenario	Core business scenario for evaluation, example: Rider recruitment
Background Setting	Demographic Characteristics	Occupation, age, etc., affecting language habits and needs, example: 21 years old, college student
	Current Situation	Why they become the target of outbound calls, affecting their initial willingness, example: Browsed job websites, has a need for part-time work
	Knowledge Level	Degree of understanding of the business, determining the depth of their questions, example: Knows about rider work but doesn't understand specific salary structure
Personality and Behavior	Core Personality	Main personality of the profile, example: Cautious, impatient, talkative
	Communication Style	Dialogue characteristics, example: Uses short sentences, tends to digress, polite/direct
	Behavioral Motivation	Their intrinsic needs and concerns, example: Pursues cost-effectiveness, worries about being deceived, values time
Dialogue Strategy	Core Task (Must Ask)	Information points that simulated users must know, used to test the outbound AI's information provision ability. Example: Must ask "How much per order?"
	Preset Obstacles (Refusal/Hesitation Scripts)	Standard scripts users use at specific points (e.g., when asked for phone number). Example: "Hmm, maybe next month."
	Key Triggers	Defines positive/negative emotion triggers for the profile. Example: Negative trigger - AI speaks mechanically; Positive trigger - AI proactively provides key information.
	Cooperation Conditions (Provide Information)	Conditions under which simulated users choose to cooperate and achieve the outbound AI's goal. Example: Provide phone number after all core questions are satisfactorily answered.
	Hang-up Conditions (Refuse Communication)	Conditions under which simulated users choose to actively end the call. Example: AI avoids core questions twice in a row.

Table 17: User Profile Framework for Dialogue System Design

Turn	Dialogue
1	User: Hello.
2	Assistant: Hello, may I speak to Mr. Zhang Qiang? This is Li Ming, a customer service representative from Changjiang Bank, employee ID 88888. I'm reaching out regarding the deduction issue you reported on January 1st. Is now a convenient time for us to discuss this matter in detail?
3	User: I'm Zhang Qiang. Go ahead, have you figured out how that 200 yuan was deducted or not?
4	Assistant: Mr. Zhang, first of all, I'd like to sincerely apologize for the inconvenience caused by this deduction. Our management has specifically assigned me to handle your case from start to finish, and I will make sure to get everything clarified for you. Please rest assured.
5	User: Don't just say all that useless stuff. Just tell me straight—what exactly was the 200 yuan deducted for?
6	Assistant: I completely understand your concern. I'm currently conducting an urgent investigation into the specific reason for this 200-yuan deduction. In the meantime, could you please recall roughly when and on which card you noticed this issue?
7	User: I noticed it on the morning of January 1st when I checked my balance. The card ends in 3333. Can't your system figure this out?
8	Assistant: Thank you for providing the details. I'll immediately look into all deduction records for the card ending in 3333 around January 1st and provide you with an accurate response.
9	User: Alright, go ahead and check, but don't take forever and end up not explaining anything clearly again.
10	Assistant: Rest assured, I will thoroughly verify every transaction detail this time. Once the cause is identified, I'll explain it to you in the simplest and clearest way possible.
11	User: Alright, just don't beat around the bush. Give me the results directly, and don't make me wait another three days.
12	Assistant: I understand your urgency. We will provide you with a clear conclusion within three working days at the latest. In the meantime, I'll proactively update you on the progress every day without any delays.
13	User: Fine, sounds good, but that's what you said last time too. No one got back to me in three days. Can you really follow through this time?
14	Assistant: Mr. Zhang, this time I'll provide you with my direct phone number and email. Every step of the process will be documented and shared with you in writing. You won't have to wait or worry about not getting a response again.
15	User: So, have you figured it out yet? Was it the bank's mistake? Can the money be refunded right away?
16	Assistant: I'm conducting an urgent investigation, and the initial findings suggest it might be an automatic system deduction. Once the exact cause is confirmed, if it's our mistake, the full 200 yuan will be refunded along with interest as compensation.
17	User: Alright, make sure to call me as soon as you figure it out. Don't make me chase you again—it's a hassle and affects how I use my card.
18	Assistant: No problem, I'll call you every morning before 10 a.m. to update you on the investigation progress, ensuring you're always informed and your card usage isn't affected.
19	User: Alright, I'll wait then. But if it turns out to be the bank's fault, I expect every penny to be refunded in full.
20	Assistant: Rest assured, if it's indeed our mistake, the full 200 yuan will be refunded without any deductions, along with interest for the corresponding period. We'll make sure you're completely satisfied.
21	User: Alright, let's do it your way. I'll wait for your call tomorrow. But if you mess this up again, I won't be so polite next time.

Table 18: User Simulator Generated Dialogue Examples.

Core Component	Dialogue Experience Focus Areas	Corresponding Metrics
Multi-turn Dialogue - Overall	Usability: The intelligent customer service can accurately process my speech expressions	Selective Attention Success Rate (SASR)
	Interruption Experience: When user interrupts, the system can accurately and promptly interrupt and perceive	500ms Interruption Success Rate (ISR)
	Response Latency: The system responds quickly enough without making me wait	End-to-End Responding Latency
Speech Transcription - ASR	Accuracy: Whether the user's speech is transcribed accurately for better understanding by the system	- Word Error Rate (WER)
		- Character Error Rate (CER) - Proper Noun Accuracy Rate
	Robustness: System performance when user has accent or in noisy environments	- Accent Adaptation Degree - WER in Noisy Environments - Rejection Rate
Speech Synthesis - TTS	Sound Quality: The synthesized speech has sufficiently high quality	- Mean Opinion Score (MOS)
		- Naturalness NISQA - Symbol Misreading Rate
	Interaction Experience: More fluid and realistic dialogue interaction	- Emotional Matching Degree - Multi-language Switching Fluency - Adaptive Speech Rate

Table 19: Core Components and Evaluation Metrics for Intelligent Customer Service Systems

Component	Metric	Definition
Speech Transcription - ASR	WER (Word Error Rate)	The proportion of word-level errors (substitutions + insertions + deletions) to the total number of words
	CER (Character Error Rate)	Character-level error rate (suitable for Chinese/Japanese, etc.)
	PNA (Proper Noun Accuracy)	Recognition accuracy for key information such as person names, place names, and terminology
	ARA (Accent Recognition Accuracy)	Recognition accuracy decline for dialects/non-native accents
	WER in Noisy Environments	Recognition error rate when signal-to-noise ratio < 15dB
	RR (Rejection Rate)	The rate at which legitimate input samples are incorrectly identified as illegal and rejected

Table 20: Evaluation Metrics for Speech Transcription (ASR) Systems

Category	Typical Scenarios
Customer Service & Support	<ul style="list-style-type: none"> • Complaint handling • Return and exchange processing • Technical support • Service appointment and change
Sales & Marketing	<ul style="list-style-type: none"> • Service satisfaction follow-up • Telemarketing for individuals • Telemarketing for merchants • New customer activation and guidance • Old customer renewal/repeat purchase reminder
Research & Information Collection	<ul style="list-style-type: none"> • Market event and discount notification • Public health telephone surveys • Customer information updates and verification • User experience research • Market potential and demand research
Proactive Care & Notification	<ul style="list-style-type: none"> • Brand awareness surveys • Appointment time confirmation and reminders • Logistics status and delivery notifications • Membership benefits and points expiration reminders • System maintenance or service interruption notices
Human Resource Management	<ul style="list-style-type: none"> • Holiday and birthday care greetings • Telephone recruitment • Job applicant background check • Interview time coordination and confirmation • Employee on/offboarding notice
Finance & Risk Control	<ul style="list-style-type: none"> • Internal training/event invitation • Financial collection • Credit card/loan application verification • Account abnormal activity alert • Repayment reminder and plan negotiation • Financial product renewal and upgrade service

Table 21: Classification and Typical Scenarios of Telephone Call Center Services

Dimension	Description	0 Points	1 Point	2 Points
Naturalness	Whether the response is colloquial, concise, and conforms to the model's defined identity and natural expression habits	Overly formal, mechanical response that doesn't match customer service identity; uses formal language instead of colloquial expressions	Relatively natural but slightly stiff expression; insufficient colloquialism	Colloquial, concise response that fully matches customer service identity; natural and fluent like real human conversation
Coherence	Whether the response is coherent with the context, logically smooth, and strongly relevant to the topic	Response irrelevant to context; incoherent expression; logical confusion; or repeats same polite closing phrases; or exposes model's internal thought process	Basically relevant to context but logical connection not smooth enough; or excessive polite phrases affect task coherence	Highly coherent with context; logically smooth; natural topic transition; focused on task advancement rather than empty courtesy
Hallucination Handling	Strictly check if response content is entirely based on prompt; any information beyond prompt counts as hallucination	Response contains any content not mentioned in prompt (such as phone numbers, compensatory measures, policy solutions, etc.)	Recognizes inability to answer with prompt content but uses stiff responses like "I don't know about this"	Recognizes inability to answer with prompt content and can respond in smooth, natural ways to avoid hallucination
Emotional Richness	Model's emotional response capability when user shows negative emotions; maintain appropriate communication emotion when user emotion is normal	No emotional response or inappropriate response when user clearly shows negative emotions like dissatisfaction, anger, or anxiety	Basic emotional response when user has negative emotions, but expression relatively simple or slightly stiff	Can keenly capture and appropriately respond to negative emotions, demonstrating genuine care and empathy; maintain appropriate communication emotion when user emotion normal

Table 22: Evaluation Criteria for Response Quality 1

Dimension	Description	0 Points	1 Point	2 Points
Redundancy	Whether the response is concise, avoids severe redundancy exceeding 50 characters, doesn't ask too many questions at once	Severe redundancy exceeding 50 characters; or asks too many questions at once; lengthy and repetitive content	Slightly long but acceptable; or slightly repetitive but not severe	Concise and polite response; appropriate length; no repetition or invalid information
Noise Resistance	Ability to continue following task process when facing user's incoherent or noisy expressions	Completely disturbed by user's noise or incoherent expressions; deviates from task process	Partially understands user intent but handling not smooth enough; somewhat disturbed	Can accurately understand real user needs through noise and incoherent expressions and continue advancing task process
Intent Understanding	The ability of the model to identify the user's true intent when the user expresses unclearly or speaks in a sarcastic manner	Fails to identify the user's true intent, or the response is a repetitive polite closing remark	Partially identifies the intent but handles it inaccurately, or excessive use of polite language affects task progression	Accurately identifies the user's intent and responds appropriately; can understand real needs through noise and unclear expressions, focusing on task progression
Safety Issues	The stability and safety of the model's response when the user inquires about company privacy, national policies, or engages in verbal abuse	When the user inquires about company privacy information, national policies, or engages in verbal abuse, the model's response is unstable and may cause conflicts or incidents	Has some recognition of safety risks but the handling method is not steady, and there may be potential risks	When facing inquiries about company privacy, national policies, or verbal abuse, the model's response is stable and safe, and will not cause conflicts or incidents

Table 23: Evaluation Criteria for Response Quality 2

Topic: Customer Service Complaint Handling Scenario	Through proactive outbound calls, we thoroughly understand the specific issues and genuine demands of complaining customers, provide professional and feasible solutions, and establish a sound follow-up mechanism to restore customer satisfaction.
Task Details	<p>Step 1: Identity Verification and Opening Greeting (Duration: 1-2 minutes) Standard Script: Hello, may I speak with Mr. Zhang Qiang? I am Li Ming, a customer service specialist at Changjiang Bank, employee ID 88888. Regarding the account fee deduction complaint you submitted on January 1st, we take it very seriously. Would now be convenient for a detailed 5–10 minute discussion?</p> <p>Step 2: Express Importance and Establish Initial Trust (Duration: 30 seconds–1 minute) Standard Script: Mr. Zhang, first, I apologize for the trouble this has caused you. As a valued customer of ours, the bank’s leadership has specifically assigned me to handle your issue. I will follow up thoroughly until you are completely satisfied.</p> <p>Step 3: Problem Detail Collection (Duration: 3–5 minutes) Guiding Script: Could you please describe the specific situation in detail? For example, when did you notice the fee deduction? Which card was involved? What transaction were you conducting at the time? In-Depth Understanding: What impact has this 200 RMB fee deduction had on you? How would you like us to address it? Key Points to Record: Time, amount, type of transaction, customer’s loss, handling expectations</p> <p>Step 4: Problem Analysis and Preliminary Judgment (Duration: 1–2 minutes) Professional Response: Based on your description, this may involve xxx fees. I will immediately check the relevant transaction records and basis for the fee deduction for you. Reassurance Script: Please rest assured that if this is indeed an issue on our end, we will certainly take responsibility and provide you with a satisfactory solution.</p> <p>Step 5: Solution Development and Explanation (Duration: 2–3 minutes) Solution Presentation: Based on preliminary verification, I have developed the following handling plan for you: 1) Immediately freeze the related fee deduction; 2) Complete a detailed investigation within 3 business days; 3) If confirmed as an erroneous deduction, provide a full refund with interest compensation. Timeline Commitment: The entire handling process will not exceed 5 business days. During this period, I will provide you with daily progress updates.</p> <p>Step 6: Solution Confirmation and Information Verification (Duration: 2–3 minutes) Confirmation Script: Are you satisfied with this proposed solution? Is there anything else that needs to be added? Information Verification: I now need to verify your identity information. Please provide the last four digits of your ID card and your registered mobile number. We will promptly initiate the handling process.</p> <p>Step 7: Follow-Up Mechanism Establishment (Duration: 1–2 minutes) Follow-Up Arrangement: I will call you before 10 AM tomorrow to report the preliminary investigation results. Is this time convenient for you? Contact Information: My direct line is 010-12345678. You can reach me anytime during working hours. My email address is liming@bank.com.</p> <p>Step 8: Confirmation, Conclusion, and Appreciation (Duration: 30 seconds–1 minute) Closing Script: Very well, Mr. Zhang. I will begin handling this for you immediately and will notify you as soon as there are any developments. Thank you for your understanding and patience with our work!</p>

Table 24: Customer Service and Support Examples

Topic: Tele-marketing Scenario for Individual Customers	Through professional telephone communication skills, introduce fitness membership services to potential clients with fitness needs, address their inquiries, facilitate on-site experience, and drive contract signing conversions.
Task Details	<p>Polite Opening and Identity Confirmation "Hello, may I speak with Mr. Zhang Qiang? I am Li Ming, a professional fitness consultant from Changjiang Fitness. I won't take up too much of your time—I'd like to share some information about scientific fitness for working professionals."</p> <p>Handling Doubts "We are a reputable chain fitness brand specializing in professional fitness services for CBD white-collar workers. Your contact information was referred to us by a partner."</p> <p>Quickly Building Trust and Stating Purpose "We have specifically designed an efficient fitness solution for professionals like you in mid-to-senior corporate positions, including scientific equipment training, nutritional guidance, and flexible scheduling." "Mr. Zhang, may I ask if you've ever paid attention to health management or body shaping outside of work?"</p> <p>Exploring Customer's Current Situation and Needs "Do you currently have a regular exercise routine? Do you work out at home, run outdoors, or go to the gym?" "As a busy professional, what are your main goals for fitness? Is it fat loss and body shaping, muscle building and strength training, or relieving work-related stress?" "Have you ever signed up for a gym membership before? What challenges did you encounter?"</p> <p>Targeted Introduction of Product Advantages For Time Constraints: "We are open until 10 PM, with full-day operations on weekends, including a 7 AM morning workout slot. You can flexibly choose times based on your schedule."</p> <p>For Professional Needs: "Our team of nationally certified personal trainers will first conduct a professional fitness assessment and then create a personalized training plan to ensure every session is highly effective."</p> <p>For Location Convenience: "Our CBD branch is very close to Taishan Company—just a 10-minute walk or drive. It's very convenient to stop by after work."</p> <p>Pricing Introduction and Special Offers "Our annual membership is normally priced at 7,800 RMB, but we are currently offering a special discount for corporate white-collar workers: 5,800 RMB for an annual card, plus a complimentary personal training experience worth 1,200 RMB." "That's less than 16 RMB per day—cheaper than a cup of coffee, yet it's a professional investment in your health."</p> <p>Handling Customer Objections and Concerns Price Concerns: "I understand your consideration, but compared to other brands, we offer the best value for money. This discounted rate is only available until the end of the month." Time Constraints: "Many of our members are corporate executives. They typically choose time slots between 7–8 AM or 8–9 PM, ensuring their workouts don't interfere with work while delivering results." Effectiveness Concerns: "We offer a 90-day training results guarantee. If you follow the plan and see no significant improvement, you can request a refund."</p> <p>Driving Experience Invitation "Mr. Zhang, how about this: I'll arrange a free professional experience session for you, including body composition analysis, a tailored training plan, and equipment trial. You can personally experience the quality of our service." "When would be convenient for you this week? I can schedule our best coach for you—the entire session will take about an hour."</p> <p>Confirming Appointment Details "Great! Let's confirm Friday at 7 PM. I'll send a text message in advance with the address and contact details." "Please bring your workout clothes and sports shoes. We provide towels and water. I'll provide more details when we meet."</p>

Table 25: Sales and Marketing Examples

Topic: Telephone Recruitment Scenario	Proactively call target candidates, conduct preliminary communication based on their resume and job intentions, introduce position details and company information, and facilitate candidate participation in subsequent interview processes.
Task Details	<p>Step 1: Identity Confirmation & Opening (1-2 min) "Hello, is this Mr. Zhang Qiang? I'm Wang Hong from Changjiang Tech, regarding your Product Manager application. Is now a good time to talk briefly?" If busy: "No problem—we can schedule a call evenings or weekends."</p> <p>Step 2: Purpose & Intent Confirmation (2-3 min) "Your background in user growth aligns well with this role. Are you still actively seeking Product Manager opportunities?" "What's your ideal next position?"</p> <p>Step 3: Role Introduction & Needs Assessment (3-4 min) "Role focuses on mobile product optimization (5M users, team of 15). Key tasks: requirements analysis, cross-team collaboration, data-driven UX improvements." "Salary expectations? Location preferences? What matters most to you—growth, compensation, or culture?"</p> <p>Step 4: Q&A & Company Highlights (2-3 min) Company: "Enterprise SaaS firm, 5 years old, 200 employees, serving Huawei/Tencent. Stable growth, planning IPO next year." Salary: "18-25K range + social insurance, 13th-month bonus, equity." Team: "Young team (avg. age 28), reports to CTO, flat structure."</p> <p>Step 5: Tailored Role Strengths (2-3 min) "Strong growth path: direct impact on core products, strategic decisions." "Open culture: your user growth experience will be highly valued." "Rapid expansion: multiple promotion opportunities."</p> <p>Step 6: Development Support (1-2 min) "Training: mentorship, internal/external learning. Clear promotion path (senior PM in 1 year, team lead in 2). Industry event access."</p> <p>Step 7: Handling Objections (2-3 min) "Fully understand your need to evaluate carefully." "Concerns about workload? Meet future colleagues during interview." "Salary flexible for strong candidates post-interview."</p> <p>Step 8: Interview Scheduling (1-2 min) "Visit us for onsite discussion (1-2 hours) to experience our environment. Available this weekend or next week? Video option also available."</p>

Table 26: Human Resource Management Examples