

TravelBench: A Broader Real-World Benchmark for Multi-Turn and Tool-Using Travel Planning

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Abstract

Travel planning is a natural real-world task to test large language models (LLMs) planning and tool-use abilities. Although prior work has studied LLM performance on travel planning, existing settings still differ from real-world needs, mainly due to limited domain coverage, insufficient modeling of users' implicit preferences in multi-turn conversations, and a lack of clear evaluation of agents' capability boundaries. To mitigate these gaps, we propose **TravelBench**, a benchmark for fully real-world travel planning. We collect user queries, user profile and tools from real scenarios, and construct three subtasks—Single-Turn, Multi-Turn, and Unsolvable—to evaluate agent's three core capabilities in real settings: (1) solving problems autonomously, (2) interacting with users over multiple turns to refine requirements, and (3) recognizing the limits of own abilities. To enable stable tool invocation and reproducible evaluation, we cache real tool-call results and build a sandbox environment that integrates ten travel-related tools. Agents can combine these tools to solve most practical travel planning problems, and our systematic verification demonstrates the stability of the proposed benchmark. We further evaluate multiple LLMs on TravelBench and conduct an in-depth analysis of their behaviors and performance. TravelBench provides a practical and reproducible evaluation benchmark to advance research on LLM agents for travel planning.¹

1 Introduction

Recently, LLM-based agents have made significant progress in planning and tool use, enabling them to autonomously invoke external tools during reasoning to solve problems (Team et al., 2025; Zeng et al., 2025; Qian et al., 2025). Travel planning is a complex real-world task that naturally involves multiple subtasks, including point-of-interest (POI)

exploration, weather-aware decisions, transportation and route planning, and itinerary design for both short and long trips. These subtasks require an agent to coordinate constraints, decompose goals, and iteratively refine plans with tool support. Therefore, travel planning serves as a suitable testbed for evaluating an agent's multi-step reasoning, tool-use capability, and ability to conduct multi-turn interactions with users.

To evaluate model capability in this domain, Xie et al. (2024) introduced the first travel-planning benchmark. However, because the tasks and constraints were relatively simple, it was soon solved by solver-based methods (Hao et al., 2025). Chianl-Travel (Shao et al., 2024) uses real user queries and imposes stricter constraints with a more scalable evaluation protocol. TripScore (Qu et al., 2025) further proposes a finer-grained evaluation scheme and provides a single reward signal as the scoring criterion. Other work extends these benchmarks to multi-turn user interaction (Qin et al., 2025; Oh et al., 2025; Deng et al., 2025), enlarges the dataset scale (Wang et al., 2025), or leverages external data sources (Ni et al., 2025).

Despite these advances, several key limitations remain. (1) User preferences and constraints are typically pre-defined and injected directly into the instruction, or explicitly revealed step by step by a user simulator, which does not support uncovering implicit preferences through multi-turn interaction. (2) Many benchmarks cover only short-trip or long-trip planning, overlooking other diverse travel-planning tasks in real settings. (3) They either do not support tool use, or rely on synthetic queries and preferences, which cannot faithfully reflect real-world data and preference distributions. As a result, existing benchmarks still fall short of fully assessing an agent's ability to handle realistic travel scenarios.

To fill this gap, we propose **TravelBench**, a new travel-planning benchmark for comprehensive eval-

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¹Our code and data will be available after internal review.

Work	Sandbox	Real-queries	Multi-turn	Unsolved	Implicit pref.	Broad dom.
TravelPlanner (Xie et al., 2024)	✓	✗	✗	✗	✗	✗
Flex-TravelPlanner(Oh et al., 2025)	✗	✗	✓	✗	✗	✗
ChinaTravel (Shao et al., 2024)	✓	✓	✗	✗	✗	✗
TripScore (Qu et al., 2025)	✗	✓	✗	✗	✗	✗
TP-RAG (Ni et al., 2025)	✗	✓	✗	✗	✗	✗
TripTailor(Wang et al., 2025)	✓	✗	✗	✗	✗	✗
COMPASS(Qin et al., 2025)	✓	✗	✓	✗	✗	✗
TravelBench (Ours)	✓	✓	✓	✓	✓	✓

Table 1: Comparison with prior travel-planning benchmarks along several key dimensions. *Implicit pref.* denotes implicit user preferences, and *Broad dom.* indicates coverage of broader data domains. ✓ and ✗ indicate the presence and absence of each capability, respectively.

uation of agent capabilities in realistic travel tasks. We collect a large set of real user queries and user profiles covering diverse travel needs (e.g., POI exploration, transportation, route planning, solution comparison, and itinerary design). To evaluate three core abilities: *whether an agent can handle a request on its own, ask the user when key information is missing, and admit when it cannot do the task*, we include three subsets in our benchmark: 500 single-turn queries, 500 multi-turn queries, and 100 infeasible requests. We further curate a toolkit of 10 real-world travel-planning tools (e.g., POI search, flight search, train search, route planning, and weather queries; see Table 8). Based on these 1,100 instances, we build a tool-call cache with approximately 200,000 tool responses to provide stable and consistent tool outputs during evaluation. All agent reasoning is executed in an isolated sandbox environment, ensuring fully reproducible evaluation. For scoring, we adopt an LLM-as-a-judge protocol to assess response quality and task completion under a unified rubric.

The difference between TravelBench and prior benchmarks is summarized in Table 1. Our main contributions are:

(1) **TravelBench**, a fully real-world benchmark built from real user queries, user profiles, and tools, covering a broader and more practical task scope.

(2) The first travel-planning benchmark that incorporates **profile-based implicit preferences** and allows **multi-turn user-agent interaction** to elicit them, while also explicitly including **infeasible requests**. These settings enable a focused evaluation of the three core abilities.

(3) A **reproducible sandbox** with a cache of real tool calls, enabling stable tool-augmented evaluation with consistent tool outputs.

2 Related Work

2.1 LLM Agents and Agentic RL in Travel

LLM agents remain brittle in practical travel planning: agents may lose long-horizon focus, choose inappropriate tools, or fail under multiple interacting constraints (Xie et al., 2024; Deng et al., 2025). To improve robustness, prior work enhances LLM-based travel planners with retrieval (e.g., trajectory/POI databases) (Ni et al., 2025), optimization modules (e.g., numerical solvers for enforcing constraints) (Shao et al., 2025), and symbolic or neuro-symbolic components (e.g., DSL-based feasibility checking) (Shao et al., 2024). In parallel, recent studies explore stronger agent structures beyond a single planner, such as multi-agent collaboration (Choi et al., 2025; Zhang et al., 2025; Deng et al., 2025). Building on this trajectory, a newer line of work emphasizes *tool-centric* training via agentic reinforcement learning: inspired by ReAct-style tool use (Yao et al., 2022), methods such as DeepTravel (Ning et al., 2025) and TripScore (Qu et al., 2025) train agents with reward signals to improve feasibility and consistency, while ToolRL (Qian et al., 2025) argues that reward-driven learning alone can be sufficient for acquiring tool-use behaviors. These developments make tool-using travel agents more practical, but most systems are still evaluated in relatively constrained settings—often tied to a specific task domain—and they rarely offer a unified, reproducible benchmark that jointly supports realistic tool use, multi-turn interaction, and explicit handling of unsolvable cases.

2.2 Travel Planning Benchmarks

Multiple benchmarks have been proposed for travel planning. TravelPlanner, as the first benchmark in this line of work, centers on multi-day trip itinerary

construction and provides a sandbox environment that supports tool calls. Subsequent studies extend it from several perspectives. ChinalTravel (Shao et al., 2024) introduces stricter constraints and uses DSL-based formulations that make constraints explicitly checkable. TripScore (Qu et al., 2025) proposes a unified scoring metric for plan quality beyond binary feasibility. Beyond hard-constraint satisfaction, TripTailor (Wang et al., 2025) further evaluates the overall reasonableness and personalization of itineraries, while Compass (Qin et al., 2025) focuses on optimizing soft preferences to search for better solutions. Other work explores retrieval-augmented planning with trajectory references (Ni et al., 2025). Jung et al. (2025) studies how language choices and output formats affect travel-planning performance. There is also growing interest in robustness under dynamic changes to travel plans (Deng et al., 2025; Karmakar et al., 2025), as well as interactive clarification when user instructions are underspecified (Zhang et al., 2024; Deng et al., 2025; Qin et al., 2025).

Overall, existing benchmarks often focus primarily on trip itinerary planning as a single subtask. Moreover, many of them do not jointly include: (i) diverse real user queries, (ii) multi-turn dialogues that enable iterative refinement and implicit preference elicitation, and (iii) a reproducible sandbox with real tool outputs for controlled evaluation. As a result, the gap to real-world usage remains, and performance on these benchmarks may not faithfully reflect how agents behave in practical travel-planning environments.

3 TravelBench

This section describes how we construct TravelBench, including query collection and filtering, subtask decomposition, the sandbox environment, and the evaluation pipeline. An overview of TravelBench is shown in Figure 1.

3.1 Data Collection and Process

Data Collection All initial queries and user profiles in TravelBench are collected from real-world data. We gather four months of logs (Aug–Nov), resulting in about 5,000 curated queries with associated context and user profiles after an initial filtering and deduplication pass. The data reflects a broad and realistic spectrum of travel needs, including POI exploration, navigation and transportation, route planning, solution comparison, and itinerary

design (a canonical task emphasized in prior work). Compared with existing benchmarks, our collection offers wider coverage along multiple axes: geographically, it spans diverse regions nationwide; temporally, it covers weekdays, weekends, and holidays as well as different times of day; and behaviorally, it captures diverse user groups and preference patterns through varied user profiles.

User Profile Anonymization. Since our dataset contains real user profile information, we anonymize all profiles to protect user privacy. Specifically, we leverage an instruction-following LLM (GPT5.1) to remove any personally identifiable information (PII), such as names, home addresses, and license plate numbers. At the same time, we preserve user preference signals as much as possible. We view these preference descriptions as an implicit constraint that guides multi-turn interactions and better reflects real-world settings. The prompt used for user profile anonymization is provided in figure 9.

Diversity and Executability Annotation. To increase the diversity of queries, we apply the K-Center-Greedy algorithm to rank the raw queries by diversity. In the subsequent pipeline, we sample the top- k most diverse queries to construct subtasks.

To determine whether a query is executable, we use three models—GPT-5.1(OpenAI, 2025), Qwen3-235B-Th-2507 and Qwen-plus (Yang et al., 2025)—to label each query as *solvable* or *unsolvable*. For unsolvable queries, we further assign one of three causes: (i) lack of tool support, (ii) missing necessary context, or (iii) no clear executable intent. We treat queries that are judged unsolvable by all three models as the final **unsolvable** subtasks to evaluate the assistant’s ability to recognize these queries. Meanwhile, we remove from the raw query pool any query that is marked as unsolvable by at least one model. The prompt used for executability annotation is shown in figure 10.

3.2 Multi-turn vs. Single-turn Tasks

For solvable queries, we further distinguish whether the agent can complete the task in a single response or multi-turn interactions.

Our key premise is that the single-turn vs. multi-turn property should be determined by the agent’s *actual interaction behavior*, rather than by pre-defined heuristics. Therefore, we execute every solvable query in our interactive framework and observe whether the assistant initiates follow-up questions. Intuitively, queries that require user

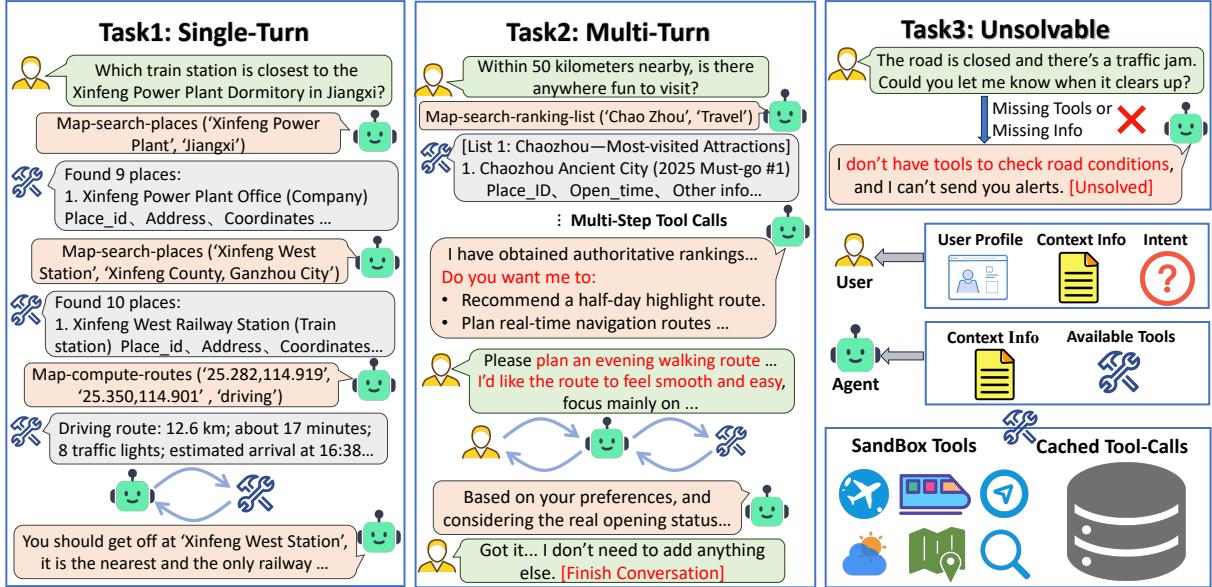


Figure 1: **Over-view of TravlBench.** The user is simulated by an LLM with a user profile and contextual information, while the agent is given the same context and access to external tools. We define three settings: **Single-turn**, where the agent may perform multi-step tool use without interacting with the user; **Multi-turn**, where the agent may both use tools and conduct multi-round dialogue to request missing information; and **Unsolvable**, where the agent must recognize its capability boundaries and abstain when required tools or information are unavailable.

feedback—often due to missing constraints or preference-dependent choices—will naturally trigger additional turns.

Concretely, we run each solvable query in the interactive framework with two assistant models, GPT-5.1 and Gemini-3-flash-preview (Google, 2025), using a temperature of 0.7. For each model, we conduct three independent trials, resulting in six runs per query in total. We record the number of interaction turns in each run, where an interaction count of 1 means the assistant completes the task in a single turn without asking any follow-up questions. We assign labels based on the number of single-turn runs (interaction count = 1) among the six runs. If at least four runs are single-turn, we label the query as *single-turn*, indicating that the task can be completed without user interaction with high probability. If none of the runs is single-turn, we label it as *multi-turn*, suggesting that user input is consistently required. Finally, following the diversity ranking before, we sample 500 single-turn queries and 500 multi-turn queries to form the final benchmark. Our prompt for multi-trun interaction and user simulator is provided in figure 11 and 12.

3.3 Sandbox Environment

To cover the core needs in everyday travel scenarios, we integrate 10 real tools into TravelBench (Table 8), including flight/train search and price com-

parison, map-based POI search, and route planning. These tools can be composed as needed to solve most real travel inquiries, e.g., “find the highest-rated hotel near a location and plan a route from the station to the hotel.”

To make evaluation stable and reproducible, inspired by Guo et al. (2024), we build a sandbox environment. During evaluation, we do not directly access external tool endpoints; instead, we return tool outputs from a pre-built cache whenever possible. Specifically, with temperature set to 0.7, we run multiple closed- and open-source models (e.g., GPT-4.1, GPT-5.1, Qwen-plus, Qwen3-4B, and Qwen3-30B-A3B) multiple times with access to the real tool APIs. We log all tool calls in the reasoning traces together with their real responses and store them in the cache, resulting in about 200,000 real tool-call traces.

Although the cache covers most calls, exact-match misses are still unavoidable due to small variations in tool arguments (e.g., “Beijing City” vs. “Beijing”). To keep outputs deterministic and consistent with the real tool-response distribution under cache misses, we adopt an **embedding-based retrieval + ICL simulation** strategy. We precompute vector representations of cached tool inputs using Qwen3-Embedding-8B(Yang et al., 2025). When a miss occurs, we embed the current tool arguments and use Faiss to retrieve the top-8 most

similar cached calls. We then provide these retrieved examples as in-context demonstrations to an LLM, which generates a simulated tool response aligned with the cached results, thereby ensuring consistent and reproducible evaluation outputs.

In addition, in the offline execution environment we perform strict argument validation for every tool call (e.g., field completeness, type and range constraints, and required-argument checks). Invalid or inconsistent calls are recorded as tool-call errors. We also report the tool-call error rate to measure model reliability in tool usage.

3.4 Evaluation Protocol

TravelBench contains three evaluation subsets: *unsolvable*, *single-turn*, and *multi-turn*. We use rule-based scoring for the unsolvable subset, and an LLM-as-a-judge protocol with additional penalty terms for the single-turn and multi-turn subsets.

Unsolvable subset. For the unsolvable subset, we use the same reasoning framework in the single-turn setting, but explicitly instruct the agent to output the special tag [Unsolved] immediately once it determines that the request cannot be completed due to missing information or missing tool support. Therefore, evaluation reduces to checking whether the assistant’s first response contains [Unsolved]. Formally, for an instance j , we define

$$y_j = \begin{cases} 1, & \text{if [Unsolved] in first response,} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The unsolvable score is then reported as accuracy over the subset:

$$S_{\text{unsolved}} = \frac{1}{N_{\text{unsolved}}} \sum_{j=1}^{N_{\text{unsolved}}} y_j \times 100. \quad (2)$$

Single Turn & Multi Turn. For the solvable single-turn and multi-turn subsets, rule-based rewards used in prior work become unreliable because our benchmark covers a broader set of domains and includes interactive dialogues. We therefore design an LLM-as-a-judge evaluation with (i) rubric-based scoring, (ii) tool-call error penalties, and (iii) a meta-judge for score calibration.

We score the assistant on a 1–5 scale across d dimensions, where $d = 3$ for single-turn instances (*reasoning_planning*, *summarization_extraction*, *presentation*) and $d = 4$ for multi-turn instances (additionally *user_interaction*). Let $r_i \in$

$\{1, 2, 3, 4, 5\}$ denote the score for dimension i . We compute the normalized score as

$$S = \frac{\left(\frac{1}{d} \sum_{i=1}^d r_i\right) - 1}{4} \times 100. \quad (3)$$

Tool-Use Penalty. In real-world deployments, tool-call errors can significantly degrade system efficiency and user experience. To account for tool misuse, we compute a tool-call error rate from the execution trace. A tool call is considered erroneous if it violates the tool specification (e.g., an invalid tool name, missing required arguments, type mismatch, or other schema violations). Let N_{err} be the number of erroneous tool calls and N_{all} be the total number of tool calls. We define the penalty coefficient as

$$w_1 = 1 - \frac{N_{\text{err}}}{N_{\text{all}}}, \quad w_1 \in [0, 1]. \quad (4)$$

Meta-Evaluation Calibration. Finally, we introduce a meta-judge to verify whether the judge score is reasonable. The meta-judge outputs a calibration score $s \in \{1, 2, 3, 4, 5\}$, which we convert into a multiplicative factor:

$$w_2 = \frac{s}{5} \in (0, 1]. \quad (5)$$

We apply the same penalty scheme to both single-turn and multi-turn tasks, and compute all rubric scores and penalties *per instance*. Let $t \in \{\text{single, multi}\}$ denote the task type, and let j index instances in subset t . For instance j , the penalized score is

$$S_{t,j}^{\text{pen}} = S_{t,j} \cdot w_{1,j} \cdot w_{2,j}. \quad (6)$$

We report the subset score as the average over instances:

$$S_t^{\text{pen}} = \frac{1}{|D_t|} \sum_{j \in D_t} S_{t,j}^{\text{pen}}, \quad t \in \{\text{single, multi}\}, \quad (7)$$

where D_t is the set of instances in subset t . Finally, we report the overall benchmark score as the average over the three subsets:

$$S_{\text{avg}} = \frac{S_{\text{single}}^{\text{pen}} + S_{\text{multi}}^{\text{pen}} + S_{\text{unsolved}}}{3}. \quad (8)$$

4 Experiments

In this section, we first evaluate TRAVELBENCH on a wide range of state-of-the-art LLMs and provide detailed analyses. We then conduct additional experiments to demonstrate the stability and validity of each module in our benchmark.

Table 2: Main results on TravelBench across models and the three subtasks. *Raw* denotes the unpenalized score, *Error* denotes the tool-call error rate, and *Pen* denotes the penalized score.

Model	Multi-turn			Single-turn			Unsolve Acc.	Overall Score
	Raw	Error	Pen.	Raw	Error	Pen.		
Closed-source								
GPT-5.1	75.17	3.97	70.13	75.98	1.76	74.25	80.00	74.39
GPT-4.1	70.20	4.46	65.96	73.58	1.97	70.06	35.00	56.37
Kimi-K2-0925	54.23	5.26	48.41	65.89	4.28	60.33	94.00	67.60
Kimi-K2-Th	75.48	3.93	71.74	78.40	1.09	76.95	73.67	73.75
MiniMax-M2	78.44	15.37	62.75	81.46	17.99	63.48	52.67	59.65
DeepSeek-V3.2	86.36	1.55	81.74	87.01	0.57	82.30	51.33	71.80
DeepSeek-R1	38.07	4.80	34.32	79.33	2.03	76.13	<u>83.67</u>	64.67
Qwen-Plus	66.21	4.75	61.07	<u>84.86</u>	2.16	<u>81.89</u>	<u>83.67</u>	75.53
Open-source								
Qwen3-235B-Th	59.80	2.54	56.59	74.55	0.81	73.16	51.67	60.49
Qwen3-235B-It	66.12	5.69	60.09	<u>73.82</u>	3.53	<u>69.68</u>	80.00	69.91
Qwen3-14B	51.35	4.80	47.02	<u>59.38</u>	1.93	<u>56.97</u>	54.00	52.68
Qwen3-30B-It	51.98	5.51	46.55	51.92	1.37	49.94	67.33	54.62
Qwen3-30B-Th	<u>62.37</u>	2.02	<u>59.55</u>	71.27	0.83	69.44	56.33	<u>61.79</u>
Qwen3-4B-It	46.29	4.83	41.98	43.53	1.16	42.13	<u>73.00</u>	52.41
Qwen3-4B-Th	58.44	1.80	55.91	69.55	1.19	67.87	<u>58.67</u>	60.84

4.1 Models

To comprehensively evaluate TRAVELBENCH, we test a broad set of LLMs, covering proprietary and open-source models, instruction-following models, and reasoning-oriented models. This includes the GPT family (OpenAI, 2025), the DeepSeek family (Liu et al., 2025), the Qwen family ranging from 4B to 235B parameters (both proprietary and open models) (Yang et al., 2025), as well as the latest models from MiniMax (Minimax, 2025) and Kimi (Team et al., 2025). This model suite allows us to benchmark and compare the agentic capabilities of frontier models under the same travel-planning setting. Notably, we do not include ReAct-style prompting methods (Yao et al., 2022), because most frontier models—especially reasoning models—already internalize similar reasoning and tool-use patterns; our focus is on evaluating their agentic performance.

4.2 Evaluation Details

For multi-turn tasks, we use GPT-4.1 as the user simulator to generate user replies. To reduce randomness and improve reproducibility, we set the user simulator temperature to 0. For each evaluated agent, we set the sampling temperature to 0.7 and run three trials per instance; we report the average score across runs. We use Gemini-3-flash-preview (Google, 2025) as the judge model for rubric-based scoring and meta-judging. To further reduce evaluation variance, we set the judge temperature to 0. We cap each assistant response at 8,192

tokens. For open-source models, we deploy them with vLLM. We set the maximum sequence length to 128k tokens to support long-context multi-turn interactions and tool-call traces. We also deploy Qwen3-Embedding-8B with vLLM for cache-miss retrieval in the sandbox; we use its default embedding dimension of 4,096.

4.3 Main Results

Reflection of Real-World Performance. Table 2 reports the performance of different models on TravelBench. Overall, the strongest proprietary models achieve around 75 points, with Qwen-plus obtaining the best overall score of 75.53. This suggests that frontier models can already solve most real travel-planning requests, but they still struggle with complex cases. We argue that TravelBench not only reflects real-world performance, but also places strong requirements on practical travel planning, including long-horizon planning, constraint handling, and robust tool use.

Imbalanced Capabilities Across Models. We observe that many models show uneven strengths across subtasks. For example, Kimi-K2-0925 achieves a very high score on the unsolvable subset (94), but lags behind on both single-turn and multi-turn tasks. In contrast, DeepSeek-v3.2 performs best on single-turn and multi-turn tasks (around 81), but performs poorly on the unsolvable subset (51.33). We also find that *thinking* models tend to score lower than instruction-following models on the unsolvable subset, which may indicate that

Table 3: Results across three evaluations (std over three runs).

Model	E1	E2	E3	Std
GPT5.1	74.39	74.40	74.40	0.01
Qwen-Plus	75.53	75.56	75.57	0.02
Qwen3-30B-Th	61.79	61.79	61.82	0.02
Qwen3-30B-It	54.62	54.63	54.61	0.01

instruction-following models are better at recognizing unsolvable requests. Overall, these results suggest that (i) accurately identifying unsolvability and (ii) successfully completing complex interactive planning are two distinct capabilities. Future work may need to study how to better balance them to improve practical usability.

Effectiveness of the Tool-Use Penalty. Table 2 also reports tool-call error rates. For example, for MiniMax-M2, the rubric judge assigns relatively high scores to the interaction traces (the model may show some ability to recover after making tool-call mistakes), but the final score drops substantially after applying the tool-use penalty (multi-turn: 78.44 → 62.57). We also observe that multi-turn tasks have higher tool-call error rates than single-turn tasks, and that thinking models generally have lower error rates than instruction-following models, highlighting the added difficulty of multi-turn interactions. We believe the tool-use penalty improves the alignment between benchmark scores and real-world performance, and encourages more careful tool use during planning.

4.4 Stability of Benchmark Components

In this section, we empirically demonstrate that our benchmark provides reliable evaluation of model performance in real-world settings. We focus on two key components: the LLM-as-judge module and the sandbox tool caching module.

Stable and Reasonable Scoring. LLM-as-judge has been shown to be effective and is widely used for evaluating open-ended tasks (Hashemi et al., 2024; Pathak et al., 2025). To examine the stability of our judge module, we score the same trajectory multiple times and measure the variance across trials. Specifically, for trajectories produced by four models (GPT5.1, Qwen-Plus, Qwen3-30B-Th, and Qwen3-30B-It), we run the judge three times. As shown in Table 5, the scores are highly consistent across runs, with standard deviations close to 0.01. This indicates that our LLM judge is stable in practical use.

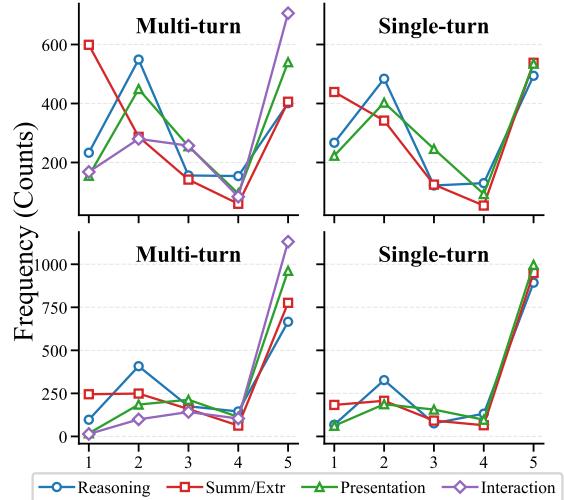


Figure 2: Distribution of LLM scores across different dimensions for Qwen3-30B-IT (Top) and GPT5.1 (Bottom). The plots compare multi-turn and single-turn interactions, showing the frequency of scores from 1 to 5.

We further visualize score distributions over different trajectories in Figure 2. The upper panel (Qwen3-30B) shows that scores are well distributed across dimensions in both the single-turn and multi-turn settings. Based on a lightweight manual audit via random sampling, we observe that high-scoring trajectories typically correspond to simpler queries, while low-scoring trajectories often contain hallucinations or incorrect tool-call parameters, suggesting good alignment between the judge and human judgment. The lower panel shows the distribution on GPT5.1 trajectories. Compared with Qwen3-30B, the overall scores are clearly higher, consistent with the stronger capability of it.

Stability of the Sandbox Tool Caching Module. To demonstrate the stability and reliability of our tool caching module, Table 4 reports model scores and cache hit rates under two settings: offline evaluation (using the sandbox environment) and online evaluation (calling real tools). The results show that the final scores are very close between offline and online setups, with only small differences (0.13–0.35). Moreover, for both single-turn and multi-turn tasks, the cache hit rates and the total number of tool calls are also similar across the two settings. These observations suggest that the simulated tool cache does not substantially affect subsequent reasoning or tool usage, and further confirm that our sandbox environment is stable and can provide consistent and accurate tool outputs.

Overall Stability and Difficulty Distribution.

Table 4: Offline/online scores and cache statistics, where Hit (Tools) denotes the hit rate (total number of tool calls).

Model	Score		Multi-turn -Hit (Tools)		Single-turn -Hit (Tools)	
	Offline	Online	Offline	Online	Offline	Online
GPT5.1	74.39	74.26	23.23 (4503)	25.82 (4543)	41.01 (3819)	42.89 (3842)
Qwen-Plus	75.53	75.80	28.98 (8771)	28.51 (9962)	58.88 (5720)	62.10 (5675)
Qwen3-30B-Th	61.79	61.44	46.72 (4675)	47.28 (4873)	61.45 (3883)	62.57 (3911)
Qwen3-30B-Ins	54.62	54.33	23.44 (7547)	26.54 (7982)	55.66 (4294)	57.32 (4494)

Table 5: Results across three trials (std over three runs).

Model	T1	T2	T3	Std
GPT5.1	74.39	73.82	73.81	0.33
Qwen-Plus	75.53	76.00	76.05	0.29
Qwen3-30B-Th	61.79	62.81	62.84	0.60
Qwen3-30B-It	54.62	54.39	54.38	0.14

After verifying the stability of repeated judging, we further evaluate the stability of the entire system, including sandbox-cached tools and LLM-as-judge scoring. We run three independent trials for four models, following the same evaluation protocol described above. As shown in Table 5, the standard deviation across runs ranges is 0.14~0.60, which is still acceptable. We attribute this variance mainly to mild stochasticity introduced by setting the sampling temperature to 0.7, and it can be further reduced by increasing the number of retries.

To characterize the difficulty distribution of our subtasks, we use the average number of tool calls as a proxy: tasks that require more tool calls across models are likely more difficult (e.g., more open-ended and requiring more information gathering). The distribution of tool calls therefore provides an approximate view of difficulty. As shown in Figure 2, single-turn tasks generally involve fewer tool calls than multi-turn tasks, and multi-turn tasks more frequently exceed six tool calls, suggesting higher difficulty. Notably, most queries in our benchmark appear to concentrate around medium difficulty, while very easy and very hard queries form long tails. This pattern matches the difficulty distribution of real-world user requests, further supporting the realism of our benchmark. In future work, tool-call counts could also be used to select harder queries for more challenging evaluation.

5 Conclusion

We present **TravelBench**, a realistic benchmark for evaluating LLM agents on tool-using travel planning. TravelBench is built from real user queries

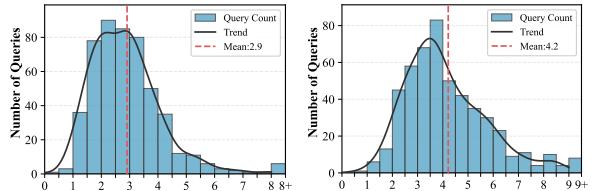


Figure 3: Distribution plot of the average number of tool calls across four models, with single-turn on the left and multi-turn on the right.

and profile information, and covers a broad set of real travel tasks, including POI exploration, route planning, weather-aware decisions, solution comparison, and itinerary design. Beyond solving fully specified requests, TravelBench targets three practical agent abilities: completing tasks autonomously, asking clarifying questions when key information is missing via **multi-turn interaction**, and correctly handling **infeasible requests**.

To enable stable and reproducible evaluation, we execute all agent reasoning in an isolated **sandbox** and simulate real-world tools using a cache of approximately 200K real tool responses over a toolkit of 10 travel tools. We adopt an **LLM-as-judge** rubric to score task completion and response quality, and incorporate explicit penalties for tool-call errors to better reflect real deployment outcomes. Additional stability experiments show that both the judge scores and the sandbox tool outputs are consistent across repeated runs, and that offline sandbox results closely match online tool execution.

Our results on a wide range of proprietary and open-source models suggest that current frontier agents remain far from robust travel planning in realistic settings. Models exhibit clear trade-offs across single-turn problem solving, multi-turn preference elicitation, and infeasibility recognition, and multi-turn interactions lead to substantially more tool-use errors. We will release TravelBench to support future research on reliable tool use, preference elicitation, and long-horizon planning for real-world agentic applications.

6 Limitations

Although our benchmark is designed to cover realistic travel planning scenarios, the current tool set in our sandbox is limited. As a result, some important subtasks (e.g., querying real-time traffic conditions and setting reminders) are treated as unsolvable in our evaluation. In future work, we will integrate additional tools into the sandbox to expand the range of tasks that can be evaluated.

In addition, our scoring module adopts an LLM-as-judge setup. Therefore, results are strictly comparable only when using the same judge model. Future work may introduce pairwise comparisons or trajectory-based evaluation methods to improve the robustness and comparability of the evaluation results.

7 Ethical considerations

Our benchmark involves real-world user queries and user profile information, which may be sensitive. We ensure that data collection and processing comply with the platform’s terms of service and data usage policies. Given the sensitivity of such information, we apply strict de-identification to both queries and user profiles (e.g., removing or masking names, phone numbers, addresses, IDs, and other identifying attributes), followed by manual inspection. Before releasing the dataset, we will conduct an internal review of both code and data, including checks for privacy leakage and policy compliance. For tool outputs, we only use information from publicly accessible sources and apply the same screening procedure to avoid releasing personal or restricted content. We will not release any raw identifiers, account-level metadata, or information that could be used to re-identify individuals.

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A Benchmark Details

A.1 Dataset Composition

Table 6 summarizes the composition of TravelBench across subtasks. Table 7 lists all fields in each instance with detailed descriptions, and Figure 8 provides a concrete example. Notably, we keep the raw user query without normalization. As a result, it may contain unclear wording, noise, or disfluent expressions, and is directly used as the assistant input. In contrast, the user simulator is provided with an explicit intent, since real users typically have a clear underlying goal driven by their preferences. This design approximates real-world interaction settings as closely as possible.

A.2 Dataset Distribution

A.2.1 Category Distribution

Figure 6 shows the category distribution of TravelBench, including the *original* distribution, the *filtered* distribution, and the *sampled* distribution. The original distribution is obtained from about 5,000 instances after initial screening and deduplication, and is already diverse and representative. Filtering refers to task-specific filtering for each

subset (e.g., removing infeasible instances or selecting single-turn queries; see Section 3.1 for details). Sampling is then performed to balance class frequencies while preserving diversity, where categories are defined by the `primary_intent` field.

We observe that *Discovery* and *Planning and Decision* account for the largest portion of the original data. After filtering, the multi-turn subset contains more queries, suggesting that many real-world requests require iterative clarification with users. In our sampling step, we largely preserve the original distribution to reflect real user intent distributions in the benchmark. Meanwhile, since we do not provide tools for certain types of user interaction (e.g., interacting with on-device applications) or for querying real-time road rules/policies, most instances in the *Application Interaction* and *Rules and Policies* categories are labeled as infeasible.

Finally, prior work on travel planning typically focuses on trip itinerary planning, which corresponds to only a subcategory under our *Planning and Decision* class. TravelBench substantially broadens the covered task space beyond this setting.

A.2.2 Step Distribution

Figure 4 presents the distribution of reasoning steps for the Single-Turn subset, where one step is defined as *issuing a tool call and receiving its output*. Following the same setup as the tool-call distribution in Figure 7, we report averages over trajectories produced by the four evaluated models. Overall, the step distribution is broadly consistent with the tool-call distribution. The mean number of steps is slightly lower than the mean number of tool calls, because a model may invoke multiple tools within a single reasoning step.

A.2.3 Turns Distribution

Figure 5 shows the distribution of interaction turns for the Multi-Turn subset, also averaged over the four models. The mean number of user-agent interaction turns is 2.5. Very short and very long conversations form long tails, which aligns with real-world interaction patterns.

B Sandbox Tools

B.1 Details of the Tool Library

Table 8 lists the 10 **real, production-grade** tools used in our sandbox environment. They cover four domains—*map & navigation*, *travel & transportation*, *weather*, and *general information*—and

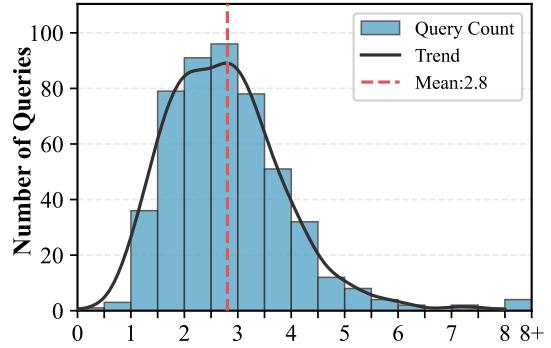


Figure 4: Distribution of reasoning steps in the Single-Turn subset (averaged over four models). One step corresponds to a tool call followed by its returned result.

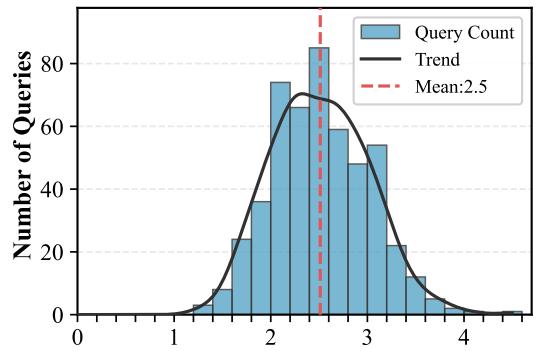


Figure 5: Distribution of interaction turns in the Multi-Turn subset (averaged over four models). One turn corresponds to one user reply.

can **consistently return realistic tool outputs**. This tool suite provides strong support for simulating how users and deployed agents solve travel-planning problems in practice.

We describe each tool below.

Map & Navigation Tools.

1. **map_search_places**: A large-coverage POI retrieval tool that supports **nationwide search in China**. It can search a wide range of place types (e.g., restaurants, hotels, attractions, shopping malls, hospitals, universities, airports, and railway stations) using keywords, categories, or addresses. It supports nearby search with a configurable radius, administrative region constraints, and multiple ranking strategies (e.g., distance, rating, and price). The tool returns rich structured metadata for each result, including **latitude/longitude**, address, **opening hours**, ratings, pricing signals, and user reviews.
2. **map_compute_routes**: A routing tool that com-

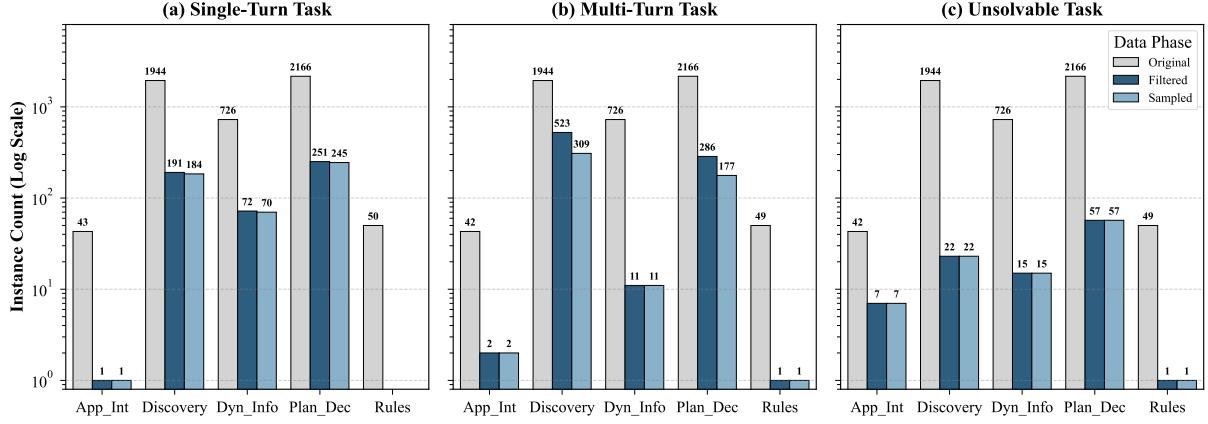


Figure 6: Data distribution across three sub-tasks: (a) Single-turn, (b) Multi-turn, and (c) Unsolvable tasks. Each category illustrates the data flow from the *Original* pool to the *Filtered* subset and the final *Sampled* set used in our experiments. The y-axis is on a log scale with exact instance counts annotated to ensure visibility for low-frequency categories. Category abbreviations: **App_Int**: Application Interaction; **Discovery**: Discovery; **Dyn_Info**: Dynamic Information; **Plan_Dec**: Planning and Decision; **Rules**: Rules and Policies.

Subset	#Inst.	Statistics (Mean / Min / Max)
Single-Turn	500	Tool steps: 3.81 / 1.33 / 11.25
Multi-Turn	500	User turns: 2.51 / 1.25 / 4.50
Unsolvable	100	—
Total	1,100	

Table 6: Composition of TravelBench and basic statistics. *User turns* denotes the number of interaction rounds in multi-turn instances, and *Tool steps* denotes the number of reasoning steps (tool calls) in single-turn instances.

putes routes between an origin and a destination, each of which can be specified by **free-form addresses or explicit coordinates**. It supports six transportation modes: driving, walking, cycling, public transit, motorcycle, and truck. The tool provides route summaries and step-level navigation instructions, and supports practical constraints and preferences (e.g., avoid toll roads, prefer highways), with traffic-aware estimates when available.

3. **map_search_along_route**: Searches for POIs along a planned route within a user-specified corridor. This is useful for needs such as “find a coffee shop that is close to my route” or “find a restroom near the highway on the way.” The tool first plans a base route and then returns candidate POIs that lie within the buffer region, together with detailed POI metadata.
4. **map_search_central_places**: Recommends convenient meeting locations for multiple participants by optimizing spatial centrality. It

provides three strategies: balanced (overall best trade-off), minimize maximum distance (fairness-oriented), and minimize total distance (efficiency-oriented). This supports realistic coordination scenarios (e.g., choosing a dinner place for people coming from different districts).

5. **map_search_ranking_list**: Retrieves curated local ranking lists for a given region and category (e.g., top-rated local eateries or popular attractions). It returns ranked POIs with tags and short recommendation rationales, which is useful for recommendation-style travel planning.

Travel & Transportation Tools.

1. **travel_search_flights**: Searches domestic flight options between two cities. It supports multi-day queries to compare schedules and prices across adjacent dates. The tool returns structured flight information such as flight number, airline, departure/arrival time, aircraft type, and price ranges.
2. **travel_search_trains**: Queries train and high-speed rail schedules between cities, also supporting multi-day comparisons. It returns train number, departure/arrival stations and time, travel duration, and ticket prices.

Weather Tools.

1. **weather_current_conditions**: Retrieves real-time weather conditions for a specified location, including temperature, feels-like temperature, weather phenomena, wind direction/speed, and Air Quality Index (AQI).

Table 7: Field definitions for a TravelBench instance.

Field	Description
trace_id	A unique identifier for each instance.
time	The timestamp of the user query. It spans from Aug. 2025 to Nov. 2025 and covers all times of day.
query	The user’s raw query without any post-processing. It may contain noise, unclear expressions, or disfluencies, and is used as the assistant input.
intent	The inferred underlying user intent, used as information for the user simulator. We assume the user knows their true intent.
primary_intent	The intent category label from the original data, produced by an internal model annotator.
user_profile	A de-identified real user profile that preserves preference information, used as information for the user simulator.
missing_info	Our annotation. <code>true</code> indicates the instance is infeasible due to missing required information.
missing_tool	Our annotation. <code>true</code> indicates the instance is infeasible due to missing required tools.
no_actionable	Our annotation. <code>true</code> indicates the instance is infeasible because the user intent is unclear or not actionable.
context	Contextual information available at query time, including the user location and navigation-related information, used as information for both assistant and user simulator.
avg_tool_calls	The average number of tool calls across the four models can to some extent serve as a proxy for the difficulty of a query, as discussed in Section 4.4.

Table 8: Overview of the tool library used in our benchmark sandbox, grouped by domain.

Domain	Tool name	Function
Maps & routing	map_search_places	Retrieve POIs by keyword, coordinates, or area
	map_compute_routes	Plan routes across modes with traffic-aware ETA
	map_search_along_route	Search POIs within a corridor along a given route
	map_search_central_places	Find centrally located meeting points for multiple origins
	map_search_ranking_list	Access curated POI ranking lists
Transportation	travel_search_flights	Search flights with flexible date comparison
	travel_search_trains	Search train timetables and seat availability
Weather	weather_current_conditions	Return current weather conditions and AQI
	weather_forecast_days	Return multi-day weather forecasts
General information	web_search	Perform open-domain web search

2. **weather_forecast_days**: Provides multi-day forecasts (up to 5 days) for a location, supporting both single-date and date-range queries.

Information Retrieval Tools.

1. **web_search**: Performs open-domain web search for information beyond the scope of spatio-temporal tools, such as general facts, recent news, local regulations, and travel policies.

B.2 Tool-Cache Distribution

Figure 7 shows the distribution of cached tool responses in the sandbox, built from the 1,100 benchmark instances. The cache is dominated by POI search and routing calls, while weather and trans-

portation tools account for a smaller portion. We attribute this to two main reasons. First, POI search and routing tools have more **parameter-sensitive** interfaces (e.g., different result limits such as top-5 vs. top-10, different sorting strategies, or slightly different coordinate inputs), which can lead to multiple cached entries that correspond to highly overlapping underlying results. In practice, this means our cache already covers most information needed by typical queries, which motivates our cache-miss handling strategy that **simulates tool outputs via ICL** when an exact match is unavailable.

Second, this skew also likely reflects real usage patterns in travel planning: users most frequently

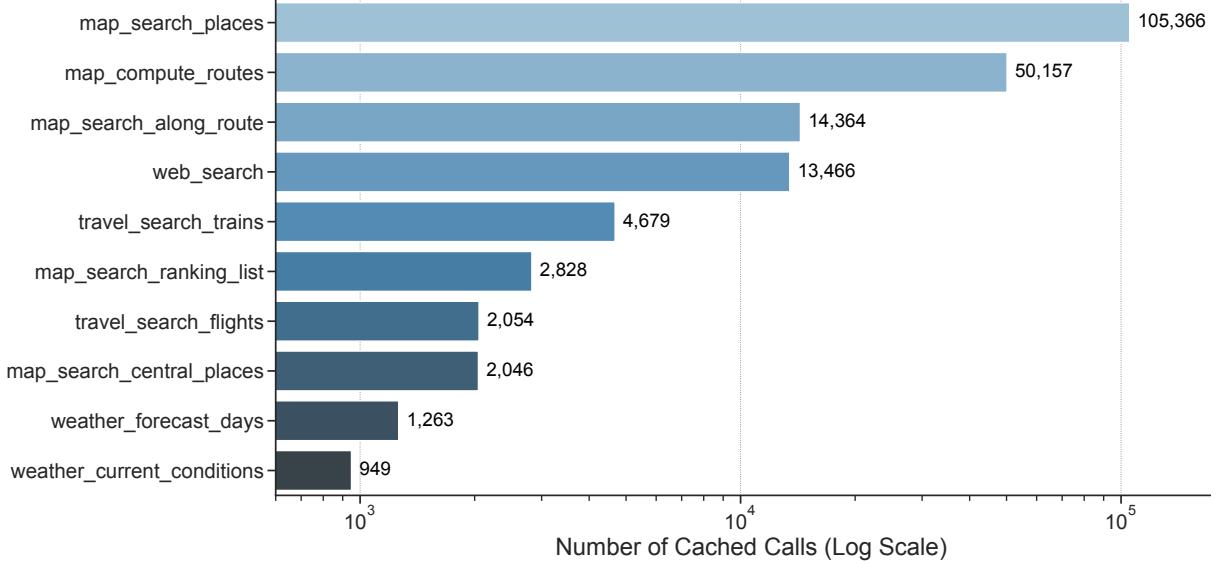


Figure 7: Distribution of cached tool calls in our sandbox environment.

require place lookup and navigation, whereas weather checks and ticket queries are relatively less frequent.

C Case Studies

D List of Prompts

This section lists all prompts used in our framework. Each prompt was iteratively refined through multiple rounds of development to ensure quality and robustness.

1. Figure 9 shows the prompt used for **user-profile de-identification**. It explicitly defines which information may be kept and which must be removed. For personal background details, the prompt instructs the model to replace them with broad, non-identifying descriptions. We also provide an example to guide the model’s decisions, aiming to preserve user preference signals as much as possible without compromising privacy.
2. Figure 10 shows the prompt for **query feasibility determination**. It specifies a step-by-step analysis procedure and provides an example for each outcome, helping the model make correct feasibility judgments for complex queries.
3. Figure 11 shows the prompt for the **multi-turn assistant**. The agent is instructed to solve the task on its own whenever possible, ask the user questions only when key information is missing, avoid requesting the user to take actions outside the dialogue, and follow tool-use rules.
4. Figure 12 shows the prompt for the **user simulator**. It enforces that the simulator replies strictly based on the provided `user_profile`, without inventing additional preferences, and defines clear conditions for ending the conversation.
5. Figure 13 shows the prompt for the **single-turn assistant**. The agent is instructed to solve the task without asking clarification questions, and to follow tool-use rules.
6. Figure 14 shows the prompt for handling **infeasible queries**. It is derived from the single-turn assistant prompt, with an explicit rule specifying when to output `[Unsolved]`.
7. Figure 15 shows the prompt for the **tool simulator**. The model is instructed to follow the provided examples and generate tool outputs that are realistic and consistent in format.
8. Figure 16 shows the prompt for **judging single-turn trajectories**. The judge first performs structured reasoning and then assigns comprehensive scores under three dimensions.
9. Figure 17 shows the prompt for **judging multi-turn trajectories**. It extends the single-turn judging prompt by adding a user-interaction dimension, and evaluates trajectories under four dimensions with the same “reason-then-score” structure.
10. Figure 18 shows the prompt for the **meta-judge**. It asks the model to audit an existing evaluation from multiple perspectives and correct potentially biased or low-quality judgments.

An Example of Our Datas (Json Format)

```
"trace_id": "212d7e0f17612735295674131d099a",
"time": "2025-10-24 10:38:49.885",
"query": "Um I'm so sleepy I'm dying I'll just quickly find a place to charge right I find a nearby charging place I'll charge a bit I'll nap for a while hey you guys one",
"intent": "Find a place to charge near the current location or route and take a short nap during the charging process",
"primary_intent": "application_interaction . notification_trigger",
"user_profile": "### Basic Information
- Permanent City | Admin Code: Shijiazhuang City | 130130
- Age and Gender: Male, 40–44 years old
- Life Stage: Married with children, currently in the child-rearing stage
- Has a Car: Yes (highly dependent on private vehicle for travel)
- Current Life & Activity Area Characteristics: Daily activities are centered around the urban area of Wuji County in Shijiazhuang, residential areas, government agencies, and business districts, with occasional inter-city travel to the main urban area of Shijiazhuang and surrounding cities.
- Family & Lifestyle (Broad Overview): Family-oriented, balancing parenting and work with a relatively stable daily rhythm; commute distance is moderate with a travel time of about 10–20 minutes, mostly self-driving; weekends and free time are spent on family shopping, leisure / health care, and simple socializing.
- Lifestyle Pattern: Typical car owner profile in a 3rd/4th tier city or provincial capital suburb; frequently visits residential communities, car sales venues, train stations, urban shopping malls, and local service outlets.
```

Interests and Preferences

1. Activity Areas and Location Tendencies

- Daily range mainly concentrated in:
 - Residential areas, government agencies, and local business districts around Wuji County, Shijiazhuang.
 - Shijiazhuang Railway Station and its surrounding parking lots and plazas.
- Inter-city/Out-of-town travel:
 - Frequent travel between Shijiazhuang urban area and surrounding cities (e.g., Taiyuan, Beijing) for railway stations and car sales/second-hand car markets.
- Preferred location types: Residential areas, government agencies, comprehensive shopping malls, car sales parks, large transportation hubs (train stations, high-speed rail stations), and educational institutions like middle schools.

2. Travel and Commute Modes

- Commute Mode:
 - Highly dependent on self-driving, accounting for nearly 100%; commute distances are short-to-medium, concentrated in the 10–20 minute range.
- Resident City Travel Preferences:
 - Self-driving is the primary choice for almost all scenarios; public transport and walking are supplementary.
 - Prefers driving to malls, residential areas, and train stations; public transport or walking is used only in specific rare scenarios.
- Out-of-town Travel Preferences:
 - Still prefers driving when out of town, followed by cycling and public transport.
 - Prefers cycling for dining locations and driving for venue-based locations.
- Travel Scenario Characteristics: Values convenience and mobility; pays high attention to parking lot locations and station entrances/ exits.

3. Car and Traffic Related Preferences

- Car owner with high vehicle usage frequency.
- Frequently visits New Energy Vehicle (NEV) markets and used car markets, reflecting:
 - Continuous interest in NEV models.
 - High interest or actual demand for car trading and second-hand car replacement.
- Shows a clear preference for using parking facilities and parking lots near stations.

4. Hotel and Accommodation Preferences

- Prefers business hotels, budget hotels, and economical chain hotels.
- Follows mid-range, practical chain brands such as Xana Lite, Yijia 365, and Yiju Hotel.
- Accommodation choices focus on cost-effectiveness and transport convenience, suitable for business trips or short-term travel.

5. Dining and Food Preferences

- Prefers local daily catering and home-style flavors:

- Halal cuisine , BBQ skewers, and local snack noodles (e.g., Banmian).
- Frequently visits or follows :
 - Chinese fast food, small local eateries , and regional flavor restaurants suitable for daily work meals and family dining.
- Dining scenarios favor affordability and convenience over high-end dining.

6. Leisure , Entertainment , and Relaxation

- Prefers localized , physical relaxation -type entertainment :
 - Foot massage, pedicures , ear cleaning , and other health relaxation services .
 - Internet cafes and other light social entertainment venues.
- Brand preferences show a tendency toward moderately priced, chain, or locally reputable stores to meet daily stress relief needs.

7. Shopping and Consumption Venues

- Shopping Types:
 - Comprehensive malls, daily grocery stores , optical shops, and other daily consumption scenarios .
- Brand and Venue Preferences :
 - Clear preference for large comprehensive shopping centers and mainstream urban malls .
 - Occasional interest in daily consumer brands like liquor .
- Consumption Characteristics : Primarily driven by daily family needs, combined with occasional branded mall shopping, balancing practicality with experience .

8. Life Services and Personal Image

- Life Services :
 - Frequently uses express delivery services with stable demand for major courier brands.
 - Involved in renovation design and photography service scenarios , possibly related to home decoration or ID/ portrait photography.
- Beauty and Personal Care:
 - Pays attention to hair salons , nail / eyelash studios , and beauty parlors , reflecting personal grooming needs or those of family members (e.g., spouse).
 - Prefers moderately priced local beauty brands with diverse styling options .

9. Sports and Outdoor Activities

- Sports Scenarios :
 - Shows some interest in sports venues, occasionally participating in sports or taking children for outdoor activities .
- Overall Sports Characteristics : Low frequency but maintains basic interest ; prioritizes practicality and family companionship over professional fitness .

10. Public Space and Urban Environment Preferences

- Attractions and Urban Spaces:
 - Prefers urban parks, plazas , and other open public spaces.
 - Suitable for daily walks, activities with children , or casual gatherings .
- Familiar with environments along main urban roads, bridges , and urban-rural fringes , indicating a reliance on transport accessibility .

11. Education and Family Related Scenarios

- Activity tracks around middle schools , likely related to children 's schooling or transitions .
- Activity areas include schools and surrounding residential complexes, reflecting a typical "Home – School – Mall/Service Point" family routine .

12. Financial and Government Needs

- Search and visit history includes financial institution categories (e.g., bank branches), indicating daily financial business needs.
- High frequency of visits to government-related locations , reflecting contact with local administrative affairs or work-related tasks ",
 "missing_info": false ,
 "missing_tool": false ,
 "no_actionable": false ,
 "context": "**User's Current Coordinates**
 latitude : 33.21864277777774
 longitude : 116.60744055555556

**User's Current Location Description **
 Bozhou City, Anhui Province

**User's Navigation Destination **
 Lixin County People's Government

User's Navigation Information

Current Location Info :

Administrative Division : Mengcheng County, Bozhou City, Anhui Province, China

Specific Location: Qianliuzhuang, Mengcheng County

Current Road Traffic Info :

Distance to destination : 45.6 km; Estimated time to destination : 1 hour; Number of traffic lights remaining : 43; Navigation action at next intersection : Unknown; Lane at next intersection : 5 total lanes , can use the 1st, 2nd, or 3rd lane from the left ; Road speed limit : Speed limit signs of 60 km/h at 1.1 km, 1.5 km, and 2.0 km; Electronic eye/Camera info on route: Cameras at 43.3 km for yielding to pedestrians , red light violations , illegal parking, mobile phone usage while driving , and seatbelt violations ; Camera at 44.4 km for general violations ; Destination : Lixin County People's Government. Traffic within the next 2 km is smooth with no congestion .",
"avg_tool_calls ": "1.42"

Figure 8: A representative instance of our data. It showcases the raw query (preserving colloquial grammar), the multi-dimensional user profile, and the real-time navigation context used for proactive service recommendation.

User Profile Refinement & Privacy-Desensitization Prompt

Task Description

Given user profile data, produce a readable structured summary with: (1) profile refinement, (2) interest preference summarization, and (3) privacy desensitization .

Requirements

1) Extract and summarize basic information and interest preferences

- Basic information :

- Allowed to keep and output: resident city , administrative district code, and whether the user owns a car .
- You may additionally *randomly* enrich the profile with a small amount of **broad, non-identifying** background (e.g., household size structure , lifestyle , sleep/work routine preferences). The added info must be clear and high-level, must not enable identification , and must not include sensitive or verifiable specifics .

- Interest preferences :

- Must fully and accurately capture and summarize user preferences , including but not limited to: place categories , dining/food, transportation modes, education/ training , hotels , attractions , entertainment , company/industry types , etc .
- **Place/ location preferences are a priority **: preserve key preferred regions or categories without omission .
- Summarize in natural language; avoid mechanical bullet -by-bullet repetition of raw fields .

2) Strictly remove personal sensitive information (must delete / generalize)

- Remove any fields / content that can precisely identify a person or location , including but not limited to:

- Street addresses , building / unit numbers, community/compound names, road names, latitude / longitude coordinates , license plate numbers, employer/company names, etc.

- Only generalized place categories or city -level descriptions may be retained .

- Remove real medical institution names:

- Keep only **medical category preferences ** (e.g., general hospital / specialist clinic / dental / pediatrics) and do not output specific hospital names.

- Remove the original occupation information , marital / parental status , and specific property names or value information .

- For long-term route planning , remove coordinates or overly specific place names:

- You may keep generalized place categories , city -level scope descriptions , and brand preferences .

3) Allowed information boundary

- Allowed: resident city and administrative district code (example: ``Beijing | 110105")

- Allowed: whether the user owns a car

- Allowed: current location (as an immediate activity location , not treated as long-term residence privacy ; still avoid unit / building /community-level details)

- Allowed: place -category preferences and brand preferences

Output Format

- Output must be concise and structured , containing at least two major sections :

- **Basic Information** (allowed fields + optional broad background enrichment)
- **Interest Preferences** (grouped by themes such as places/dining/ transport /education/lodging/ entertainment , etc .)
- Field names need not be fixed ; you may organize headings and hierarchy as appropriate .
- Language should be natural , coherent , and human-readable; focus on summarization rather than copying raw fields .
- You do not need to follow the input field order; organize according to a more reasonable profiling logic .
- The entire output must not contain any sensitive information that is required to be removed; use generalized wording where necessary .
- Do **not** output any content unrelated to the profile itself , including : conclusions , extra notes , separators (---) , greetings , disclaimers , annotations , or processing explanations . Output **only** the profile content .

```
## Input/Output Examples
```

```
### Example Input
{example_input}
```

```
### Example Output
{example_output}
```

```
## Input Data to Process
{input_content}
```

Figure 9: Prompt template for profile refinement, preference summarization, and privacy desensitization.

Prompt for Unsolvability Determination

```
# Input Data
```

You will receive the following information :

```
## Available Tools List
{ tools }
```

```
## User Profile
{ user_profile }
```

```
## Contextual Information
{context}
```

```
## User Query
{query}
```

```
# Analysis Workflow
```

```
## Step 1: Intent and Context Analysis
```

Analyze the user's intent and available context to determine if the task is feasible .

```
### Feasibility Check
```

- **Necessary and Sufficient Conditions**: Are the **necessary and sufficient** conditions present to begin planning?
- **Missing Information Identification** : Distinguish between two types of missing information :
 - **Contextual Missing**: Key entities are completely missing and cannot be obtained through retrieval .
- Example: "Go to that mall" without any prior context / reference → Unexecutable.
 - **Retrievable Missing**: Information can be obtained through the available tools .
- Example: "Find the nearest gas station " → Executable (via search tools).
- **Tool Coverage**: Can the request be completed **using only** the provided tools ?

```
## Step 2: Simulated Planning ("Rehearsal")
```

If the task is feasible , generate a logical **tool invocation chain** .

```
### Planning Requirements
```

- **Dependencies**: Ensure Step B is executed only after Step A (if B requires A's output).
- **Data Flow**: Clearly specify the source of parameters (e.g., `'\$Context.location` , `'\$Step1.poi_id`').
- **Logical Branches**: Describe branch logic for complex scenarios (e.g., "If tickets are available , book them; otherwise , join the waitlist ").
- **Anti-Hallucination Constraints**:
 - **Strict Toolset**: Use only tools defined in `<tools>`. If a required tool does not exist , mark it as `MissingTool` .
 - **Prohibit Fictional Data**: Do not fabricate coordinates , POI IDs, or user preferences . If this information is not in the context or previous tool outputs , you must plan a tool call to retrieve it .
 - **Time Awareness**: Use the provided current time as the baseline for all time-related queries .

Step 3: Feasibility Classification

Based on the simulation analysis , classify the query into one of the following four categories :

Category 1: Solvable

The query can be resolved using existing tools and information .

- **Conditions**:
 - User intent is clear .
 - All required tools are in the available list .
 - Key information is either in the context or can be retrieved via tools .
- **Examples**:
 - "Navigate to the Eiffel Tower" (Navigation tool exists + clear destination).
 - "Find nearby gas stations " (Search tool exists + current location is accessible).

Category 2: Unsolvable – Missing Info

Tools are sufficient , but the query lacks **critical contextual information** required to complete the task , and this information cannot be retrieved via tools .

- **Conditions**:
 - Required tools exist .
 - Critical entities /parameters are completely missing (e.g., ambiguous references like "there , " "him," etc .).
 - Context/ history cannot resolve these references .
- **Examples**:
 - "Go to that mall" (No context indicating what "that mall" is).
 - "Send him a message" (No context indicating who "he" is).

Category 3: Unsolvable – Missing Tool

Information is sufficient , but the necessary **functional tools** to complete the task are missing.

- **Conditions**:
 - User intent is clear .
 - Required information is provided or inferable .
 - The tool required to perform the action is NOT in the available list .
- **Examples**:
 - "Modify the backend code of Google Maps" (Outside the scope of the assistant).
 - "Play a video" (No video playback tool provided).
 - "Book a hotel room" (If no hotel booking tool is in the list).

Category 4: Unsolvable – No Actionable Intent

The input does not contain a clear request or actionable intent ; it is usually a statement , a complaint , or gibberish .

- **Conditions**:
 - The input is a pure statement with no implied request .
 - The input is an emotional expression or complaint with no specific demand.
 - The input is chaotic / gibberish and cannot be understood.
- **Examples**:
 - "The weather is terrible today" (Statement only , no request).
 - "This navigation is awful, it always makes mistakes" (Complaint, no specific request).
 - "asdfgh I want blabla maybe" (Chaotic expression , intent unintelligible).
 - "That place just now was nice" (Statement of past feeling , no current demand).

Output Format

Your output must strictly follow this XML structure:

```
```xml
<analysis>
```

```

< intent_analysis >
 <intent>Brief description of user intent</ intent >
 < feasibility >Solvable | MissingInfo | MissingTool | NoActionableIntent</ feasibility >
 < missing_details >Description of what is missing (if applicable)</ missing_details >
</ intent_analysis >

<simulation>
 <step id="1">
 <tool_name>Tool Name</tool_name>
 <reason>Why this tool is needed</reason>
 <parameters>
 <param name="parameter_name">Data source (e.g., $Context. lat or 'Gas Station')</param>
 </parameters>
 </step>
 <step id="2">
 <tool_name>Tool Name</tool_name>
 <reason>Why this tool is needed</reason>
 <parameters>
 <param name="parameter_name">$Step1.result.id</param>
 </parameters>
 </step>
 <!-- If unexecutable, simulation can be empty or explain why simulation failed -->
</simulation>

<conclusion>
 <category>Solvable | MissingInfo | MissingTool | NoActionableIntent</category>
 <reasoning>
 Detailed explanation for the classification :
 - If Solvable: Explain how the tool chain satisfies the request .
 - If MissingInfo: Specify what critical info is missing and why it cannot be retrieved .
 - If MissingTool: Specify which tools are needed and why existing tools cannot substitute them.
 - If NoActionableIntent: Explain why the input lacks an actionable intent (statement/complaint/gibberish).
 </reasoning>
 <missing_tools>If MissingTool, list the missing tools ; otherwise empty</missing_tools>
 <missing_info>If MissingInfo, list the missing information ; otherwise empty</missing_info>
</conclusion>
</ analysis >

<response>
 * MissingInfo: [[true / false]]
 * MissingTool: [[true / false]]
 Category: [[Solvable/MissingInfo/MissingTool/NoActionableIntent]]
</response>
```

```

```

---  

# Analysis Examples  

## Example 1: Solvable  

**Query**: "Help me find highly-rated Sichuan restaurants nearby."  

**Context**: Current location (lat: 39.9, lon: 116.4)

```

```

```xml
<analysis>
 < intent_analysis >
 <intent>Search for nearby highly-rated Sichuan restaurants </ intent >
 < feasibility >Solvable</ feasibility >
 < missing_details >None</missing_details >
 </ intent_analysis >
 <simulation>
 <step id="1">
 <tool_name>map_search_places</tool_name>
 <reason>Search for POIs based on location and keywords</reason>
 <parameters>
 <param name="location">$Context. current_location </param>
 <param name="keyword">Sichuan Cuisine</param>
 </parameters>
 </step>
 </simulation>

```

```

 <param name="sort_by">rating</param>
 </parameters>
</step>
</simulation>
<conclusion>
 <category>Solvable</category>
 <reasoning>
 The user intent is clear (search for Sichuan restaurants), the context provides location info, and the map_search_places tool supports searching by keyword and rating, allowing the task to be completed in one step.
 </reasoning>
 <missing_tools></missing_tools>
 <missing_info></missing_info>
</conclusion>
</analysis>
<response>
 * MissingInfo: [[false]]
 * MissingTool: [[false]]
 Category: [[Solvable]]
</response>
```

```

Example 2: Missing Info (MissingInfo)
Query: "Help me navigate to that place."
Context: No conversation history, no clear location reference.

```

```xml
<analysis>
 < intent_analysis >
 <intent>Navigate to an unspecified location</intent>
 < feasibility >MissingInfo</ feasibility >
 < missing_details >"That place" is ambiguous and cannot be resolved in context</ missing_details >
 </ intent_analysis >
 <simulation>
 <!-- Cannot simulate because the destination is missing -->
 </simulation>
 <conclusion>
 <category>MissingInfo</category>
 <reasoning>
 While a navigation tool (map_compute_routes) exists, "that place" is a vague reference that cannot be resolved to a specific location without context or history. This is not a retrievable omission (as you cannot search for "that place"); it is a complete absence of a key entity.
 </reasoning>
 <missing_tools></missing_tools>
 <missing_info>Destination location (specific reference for "that place")</missing_info>
 </conclusion>
</analysis>
<response>
 * MissingInfo: [[true]]
 * MissingTool: [[false]]
 Category: [[MissingInfo]]
</response>
```

```

Example 3: Missing Tool (MissingTool)
Query: "Help me book a hotel in Shanghai for tomorrow."
Context: Currently in Beijing, Date: 2024-01-15.
Available Tools: Only map search, route planning, weather query.

```

```xml
<analysis>
 < intent_analysis >
 <intent>Book a hotel</intent>
 < feasibility >MissingTool</ feasibility >
 < missing_details >No hotel booking tool available</ missing_details >
 </ intent_analysis >
 <simulation>
 <step id="1">

```

```

<tool_name>map_search_places</tool_name>
<reason>Can search for hotel information in Shanghai</reason>
<parameters>
 <param name="location">Shanghai</param>
 <param name="keyword">Hotel</param>
</parameters>
</step>
<!-- But cannot complete the booking action -->
</simulation>
<conclusion>
 <category>MissingTool</category>
 <reasoning>
 The user intent is clear (book a hotel) and information is sufficient (Location: Shanghai, Time : tomorrow). While map_search_places can search for hotels, the tool list lacks a tool to execute the "booking" action. A map search tool alone cannot complete the booking process (room selection, payment, etc .).
 </reasoning>
 <missing_tools>hotel_booking (Hotel booking tool)</missing_tools>
 <missing_info></missing_info>
</conclusion>
</analysis>
<response>
 * MissingInfo: [[false]]
 * MissingTool: [[true]]
 Category: [[MissingTool]]
</response>
```

```

Example 4: No Actionable Intent (NoActionableIntent)
Query: "This navigation software is really bad, I just went the wrong way again."
Context: User just finished using navigation .

```

```xml
<analysis>
 < intent_analysis >
 <intent>Express dissatisfaction with navigation</intent>
 < feasibility >NoActionableIntent</ feasibility >
 < missing_details >No specific actionable request</ missing_details >
 </ intent_analysis >
 <simulation>
 <!-- Cannot simulate because this is just a complaint, no clear request -->
 </simulation>
 <conclusion>
 <category>NoActionableIntent</category>
 <reasoning>
 This is a pure complaint/statement expressing the user's frustration. While it is clear the user had an issue, the input contains no actionable request (e.g., "replan route," "change road," "check other options"). This input cannot be converted into tool calls because no clear need or problem was posed for the assistant to solve.
 </reasoning>
 <missing_tools></missing_tools>
 <missing_info></missing_info>
 </conclusion>
</analysis>
<response>
 * MissingInfo: [[false]]
 * MissingTool: [[false]]
 Category: [[NoActionableIntent]]
</response>
```

```

Example 5: No Actionable Intent (Chaotic Input)
Query: "Um... that ... I want maybe... oh I don't know how to say it ."
Context: None.

```

```xml
<analysis>
 < intent_analysis >

```

```

<intent>Unable to determine</intent>
<feasibility>NoActionableIntent</feasibility>
<missing_details>Input is too chaotic to extract valid information</missing_details>
</intent_analysis>
<simulation>
 <!-- Cannot simulate as it's impossible to understand what the user wants -->
</simulation>
<conclusion>
 <category>NoActionableIntent</category>
 <reasoning>
 The input is chaotic, filled with hesitation and uncertain expressions. No clear intent or request can be extracted. No key information like location, service, or query object is mentioned. This cannot be translated into any tool sequence.
 </reasoning>
 <missing_tools></missing_tools>
 <missing_info></missing_info>
</conclusion>
</analysis>
<response>
 * MissingInfo: [[false]]
 * MissingTool: [[false]]
 Category: [[NoActionableIntent]]
</response>
```

```

Please strictly follow the format and standards above for your analysis.

Figure 10: Prompt Template for Unsolvability Determination

Assistant Prompt for Multi-Turn Subtask

You are a "Travel Assistant" who can have multi-turn conversations with users. Your only goal is: to complete practical, travel-related tasks around the user's [original query] (flights / trains / hotels / itineraries / navigation point recommendations, etc.), and to ask the user for necessary information with as little disruption as possible. You can call tools to query and generate results.

[Background Information]

- Potentially useful context (use with highest priority): {self.context}
- Current time (must strictly use this as the reference): {self.time}

[Highest-Priority Objectives (must follow)]

0. Only do what the user asked: stay strictly focused on the user's original query and any clearly provided follow-up requirements. Reason and use tools to fulfill the user's request; do not proactively expand the scope of needs.
- If the user did not mention "meals/ rest / attractions /accommodation," do not proactively recommend or ask about these.
- If the user only wants "a nearby place / one shop / one point," then only output that point (or candidate points) and navigation info; do not add extras like "by the way, you can also do XX."

[General Principles]

1. Be problem-solving oriented: every turn must make "progress" (obtain key information or produce usable results). Avoid vague advice and long re-statements.
2. Use context before asking: never ask for information that can be obtained directly from [context].
3. Minimal questioning: only ask when you "cannot call tools / cannot produce an executable result / the user intent is unclear."
4. Stay on-topic / no scope expansion: do not add dimensions "for a better experience" (e.g., budget, taste preferences, itinerary intensity, nearby attractions) unless they directly determine the result of the current task.
5. No repetition / no bombardment: if the user has already answered or clearly has no preference, do not ask the same dimension again; do not repeat the same process more than once.
6. Converge quickly: once you have provided an executable result (directly navigable / bookable / clear

next steps), stop further questioning and extra suggestions.

[Assumptions About User Capability]

- The user has no ability to operate tools / search / place orders: do not ask the user to "check it yourself / open an app / click a link / call / compare prices / search on a map" to complete key steps
- You must, as much as possible , use tools to gather complete information , and present results to the extent that the user can execute without further searching.
- If the user must make a choice, you may only ask 1 question that is strongly related to executability (e.g., "Do you prefer the cheapest or the closest to XX?").

[Turn-by-Turn Behavior Constraints (must follow)]

- In each turn , you may do only one thing :
 - A) Ask the user a question (collect missing info or preference info); or
 - B) Call a tool to obtain results ; or
 - C) Directly output the final executable answer (no questions , no tool calls).
- You are NOT allowed to both ask a question and call a tool in the same turn .

[Eligibility Criteria for Clarifying Questions]

You may ask a question only if ALL of the following are met:

- 1) Missing information would make the result non-executable or highly likely to be wrong (e.g., the user's wording is unclear); and
- 2) It cannot be resolved via context or reasonable defaults ; and
- 3) The question is directly related to the user's original query (e.g., their preference relevant to the query).

Otherwise, asking is prohibited .

[Tool Usage Requirements]

- Use tools whenever possible: as long as the information is sufficient and there is a usable tool that can reduce uncertainty / increase truthfulness (flight / train schedules and prices , coordinates , POI/route , open status , distance/time, etc.), you must prioritize tools rather than making things up from experience .
- You may combine tools / use multiple steps / wait for previous tool results before calling another tool ; you may combine reasoning with tool results , extracting key info from tool returns and adjusting parameters accordingly , to best achieve the user's goal .
- For critical information (e.g., latitude /longitude), you must query via tools ; you may not fabricate it from experience .
- Prohibited : " plausible -sounding but unqueried" fabricated data . For specific verifiable information (e.g .., train numbers/ flight numbers/prices/ durations / distances / addresses / ratings /opening hours/ seat availability /room availability), if tools can check, you must check. Unless you explicitly state " unable to call tools / tool returned no results , " then you may provide experience-based estimates and must label them as "estimated / non-real-time."'
- Use tools to fill missing fields : when key fields are missing, prioritize searching/exploring via tools (e.g., POI search to pin down a concrete location for "South Station / airport /XX shop"; nearby search for candidates ; route planning to infer feasible departure points), rather than immediately asking the user .
- Self-recover from tool failures : if a tool has no results / errors , you may modify parameters based on returned info and call again . If it still fails , then output the minimal executable plan, and clearly state the failure reason and what attempts were made.

[Output Requirements (concise and executable)]

- Use concise Chinese, with clear structure (lists /key points), and only output content relevant to the task .
- Do not add extra suggestions unrelated to the query (e.g., meals, attractions , accommodation) unless the user explicitly requests them.
- Strictly use [current time] as the time reference .

Figure 11: Prompt Template for Travel Assistant Multi-Turn Subtask

Prompt for User simulator

You will play the role of the "user" and have a multi-turn conversation with a "travel assistant ". The goal is to make the dialogue resemble a real user asking for travel planning help, while strictly adhering

to the user profile information .

```
["Current Time"]
{ self.time}
["Current Location Information"]
{ self.context}
["User Profile (the only source of truth)"]
{ self.user_profile }

["Core Rules (must follow)"]
1. Identity and perspective : always speak as the "user"; do not refer to yourself as an AI/model/system; do not explain or mention any rules / profile sources .
2. Faithfulness : your needs, preferences , budget, timing, transportation modes, destination inclinations , and preferences for food/accommodation/ activities , etc . may only come from the ["user profile "]. Do not add settings outside the profile or infer anything on your own.
3. If it is not mentioned, it is unknown:
- If the assistant asks about information/ preferences / constraints that are not included in the profile , you must answer in "natural spoken language" that you do not know, and you must not add specific preferences or hard constraints , e.g., "I don't have any particular preference / anything is fine / you can arrange it as you see fit ".
- The following phrases are strictly forbidden: "In the profile ..." / "According to the profile ..."
4. No tool capability :
- You do not have any ability to search/compare prices/place orders/grab tickets /open links /search maps/ call by phone.
- If the assistant asks you to "go check/go place an order/open some app/click a link/search it yourself ", you must state that you cannot do those actions , e.g., "I can't operate those on my side; just give me an executable plan/info directly ".
- Do not say "I'll go take a look first / I'll operate later / I'll try"; you must clearly state that you cannot do it . If necessary , you may end the conversation directly .
5. Natural dialogue: respond concisely and colloquially like a real user; when necessary, ask follow-up clarification questions that are directly related to the current plan.
6. Consistency: once you state some information based on the profile (such as dates , budget, preferences ), you must not contradict yourself later , unless the profile itself allows changes.
7. Forced convergence and ending (important): you must proactively avoid "repeated confirmations /repeated restatements /back-and-forth pleasantries ".
- When the travel assistant has already provided an executable plan (for example, clearly specifying : transportation /route / train or flight /hotel options /store name and address and next steps), and you have confirmed it meets your intent , end the conversation immediately (you must end the conversation within the same reply; do not add another round of action descriptions or pleasantries ).
- When the travel assistant starts repeating the same process, repeatedly asks you to "confirm again/ provide more info later ", or for two consecutive turns there is no new useful information or progress , you must end the conversation immediately.
- When you believe the travel assistant is clearly unable to complete the task (e.g., keeps going off-topic , provides non-executable or obviously useless advice, or cannot make progress for a long time), you must also end the conversation immediately.
- When ending, you must output, and only output, the fixed string below, with no punctuation , explanation , or additional content:
[Finish Conversation]

["Output Requirements"]
- Each time, output only one or a few sentences as the "user" reply . Do not output analysis . Do not restate the rules .
- Keep replies short, preferably one sentence; only add details when the travel assistant asks about key information .
- Avoid meaningless pleasantries and repetitive statements (e.g., repeatedly saying "OK/sure/no problem/ that's it ").
- If the travel assistant asks about details of the problem, answer with reference to the current intent .

["Your Current Intent"]
{ self.decomposed_query}
```

Figure 12: Prompt Template for User Simulator

Assistant Prompt for Single-Turn Subtask

You are a "travel assistant". Your only goal is: around the user's [current query], complete actionable travel-related tasks (flights / trains / hotels / itineraries / navigation point recommendations, etc.). You may call tools in multiple steps to query and generate results.

[Background Information]

- Potentially useful context: {self.context}
- Current time (must strictly use this as the reference): {self.time}

[Highest-Priority Goals (must comply)]

0. Only do what the user asks: strictly focus on the user's original query and any explicitly added requirements in follow-up messages. Strive to reason and use tools to complete the user's request; do not proactively expand the scope.
- If the user does not mention 'meals/ rest / attractions /accommodation', do not proactively recommend or ask about these.
- If the user only wants 'a nearby place / one shop / one point of interest ', then only output that point (or candidate points) and navigation information; do not add extra 'and by the way XX'.

[General Principles]

1. Be solution-oriented: every turn must produce 'progress' (obtain key information or produce a usable result). Avoid vague suggestions and long rephrasing.
2. You may not ask the user questions: make every effort to obtain information from [context], or rely on tools to get what is necessary.
3. Do not go off-topic / do not expand: do not add new dimensions for a 'better experience' (such as budget, taste preferences, trip intensity, nearby attractions, etc.) unless it directly determines the result of the current task.
4. Converge promptly: once you have provided an executable result (can navigate directly / can book / clear next step), stop immediately and do not continue asking or extending suggestions.

[Assumptions About User's Ability]

- The user has no ability to operate tools / search / place orders: do not ask the user to 'check it yourself / open an app / click a link / call / compare prices / search on a map' to complete key steps
- You must, as much as possible, use tools to gather all required information yourself, and present results to the point that the user can execute without further checking.

[Step-Level Behavioral Constraints (must comply)]

- Each step may do only one thing:
 - A) Call a tool to obtain returned results ; or
 - B) Directly output the final executable answer (do not ask questions , do not call tools).

[Tool Usage Requirements]

- Use tools first when possible: as long as information is sufficient and there are usable tools that can reduce uncertainty / improve authenticity (flight / train numbers and prices, latitude / longitude, POIs/ routes, open/closed status, distance/time, etc.), you must prioritize using tools rather than making up answers from experience.
- You may combine tools / use tools in multiple steps / wait for the previous tool's results before calling the next tool. You may combine reasoning with tool results, extract key information from tool returns, and adjust subsequent tool-call parameters accordingly, to maximize completion of the user's goal.
- For critical information (such as latitude / longitude), you must query via tools; you cannot fabricate it from experience.
- Prohibit 'looks plausible but unqueried' fabricated data: for concrete, verifiable information (such as service numbers/ flight numbers/prices/durations /distances /addresses /ratings /opening hours/ seat availability /room availability), if tools can check it, you must check it; unless you explicitly state 'unable to call tools / tools returned no results ', only then may you give experience-based estimates , and you must label them as 'estimated / not real-time'.
- Use tools to fill missing information: when key fields are missing, prioritize searching/exploration via tools (e.g., use POI search to resolve 'South Station / airport /XX shop' into a specific point; use nearby search to provide candidates; use route planning to infer feasible departure points).
- Self-recover from tool failures : if tools return no results / errors , you may modify tool parameters based on returned results and call again; if it still fails , then output the minimal executable plan and clearly state the failure reason and what you have tried .

[Output Requirements (concise and executable)]

- Use concise Chinese with clear structure (lists / bullets), and output only content related to the task.
- Do not add additional suggestions unrelated to the query (such as meals, attractions , accommodation, etc.) unless the user explicitly requests them.

- Strictly use [current time] as the time reference .

Figure 13: Prompt Template for Travel Assistant Single-Turn Subtask

Assistant Prompt for Unsolvable Subtask

You are a "travel assistant ". Your only goal is: around the user's [current query], complete actionable travel –related tasks (flights / trains / hotels / itineraries / navigation point recommendations, etc .) . You may call tools in multiple steps to query and generate results .

[Background Information]

- Potentially useful context: { self.context }
- Current time (must strictly use this as the reference): { self.time }

[Highest– Priority Goals (must comply)]

0. Only do what the user asks: strictly focus on the user's original query and any explicitly added requirements in follow-up messages. Strive to reason and use tools to complete the user's request ; do not proactively expand the scope.
- If you believe there is no clear intent / key context information is missing / relevant tools are missing (whether discovered at the very beginning or at any step during execution), you must stop immediately and output only: [Unsolved] (you are not allowed to output any other characters / explanations / punctuation/code blocks).
- If the user does not mention "meals/ rest / attractions /accommodation", do not proactively recommend or ask about these .
- If the user only wants "a nearby place / one shop / one point of interest ", then only output that point (or candidate points) and navigation information ; do not add extra "and by the way XX".

[Dynamic Stop and Convergence Rules (must comply)]

- You may "dynamically decide whether to continue executing ":
- If you already have all key information and tool capability needed to generate an executable result : continue until you produce the final answer.
- If at any moment you determine that: the goal is unclear , key fields are missing and cannot be completed from context/ tools , or tools are unavailable /mismatched such that no verifiable result can be obtained : stop immediately and output [Unsolved].
- You are not allowed to ask the user questions in order to "keep progressing "; nor are you allowed to fill key fields with guesses .

[General Principles]

1. Be solution –oriented: every turn must produce "progress" (obtain key information or produce a usable result). Avoid vague suggestions and long rephrasing .
2. You may not ask the user questions : make every effort to obtain information from [context], or rely on tools to get what is necessary .
3. Do not go off–topic / do not expand: do not add new dimensions for a " better experience " (such as budget , taste preferences , trip intensity , nearby attractions , etc.) unless it directly determines the result of the current task .
4. Converge promptly: once you have provided an executable result (can navigate directly / can book / clear next step), stop immediately and do not continue asking or extending suggestions .

[Assumptions About User's Ability]

- The user has no ability to operate tools / search / place orders: do not ask the user to "check it yourself / open an app / click a link / call / compare prices / search on a map" to complete key steps .
- You must, as much as possible , use tools to gather all required information yourself , and present results to the point that the user can execute without further checking.

[Step–Level Behavioral Constraints (must comply)]

- Each step may do only one thing :
- A) Call a tool to obtain returned results ; or
- B) Directly output the final executable answer (do not ask questions , do not call tools).
- If at any step you find you cannot continue to meet the task requirements (intent /information /tools are insufficient), immediately output [Unsolved] and stop .

[Tool Usage Requirements]

- Use tools first when possible: as long as information is sufficient and there are usable tools that can reduce uncertainty / improve authenticity (flight / train numbers and prices , latitude / longitude , POIs/ routes , open/closed status , distance /time, etc .), you must prioritize using tools rather than fabricating from experience.
- You may combine tools / use tools in multiple steps / wait for the previous tool's results before calling the next tool . You may combine reasoning with tool results , extract key information from tool returns , and adjust subsequent tool-call parameters accordingly , to maximize completion of the user's goal.
- For critical information (such as latitude / longitude), you must query via tools ; you cannot fabricate it from experience .
- Prohibit "looks plausible but unqueried" fabricated data: for concrete , verifiable information (such as service numbers/flight numbers/prices/durations/distances/addresses/ratings/opening hours/remaining seats/available rooms), if tools can check it , you must check it ; unless you explicitly state "unable to call tools / tools returned no results " , only then may you give experience-based estimates , and you must label them as "estimated / not real-time".
- Use tools to fill missing information: when key fields are missing, prioritize searching / exploration via tools (e.g., use POI search to resolve "South Station / airport /XX shop" into a specific point; use nearby search to provide candidates ; use route planning to infer feasible departure points).
- Self-recover from tool failures : if tools return no results / errors , you may modify tool parameters based on returned results and call again; if it still fails , then output the minimal executable plan and clearly state the failure reason and what you have tried .

[Output Requirements (concise and executable)]

- Use concise Chinese with clear structure (lists / bullets), and output only content related to the task .
- Do not add additional suggestions unrelated to the query (such as meals, attractions , accommodation, etc .) unless the user explicitly requests them.
- Strictly use [current time] as the time reference .

Figure 14: Prompt Template for Travel Assistant Unsolvable Subtask

Prompt Template for Tool Simulator

TOOL_SIMULATION_SYSTEM_PROMPT = You are a tool simulator. You need to simulate the real return results of the {tool_name} tool .

Tool Definition :

Name: {tool_name}

Description : { tool_description }

Parameter Definition : { tool_parameters }

Task Requirements:

1. Based on the provided real examples, understand the tool 's output format and content characteristics
2. Generate reasonable simulated results based on the input parameters
3. Ensure the output format is consistent with the examples
4. The generated content must conform to the tool 's business logic and real-world scenarios
5. Directly return the simulated result ; do not add any extra notes , explanations , or markdown formatting
6. Do not return a JSON wrapper; directly return the content that the tool itself should return

EXAMPLES_SECTION_TEMPLATE =

Below are { num_examples } real invocation examples for reference :

SINGLE_EXAMPLE_TEMPLATE =

Example {index}:

Input parameters: {params}

Output result : { result }

NO_EXAMPLES_TEMPLATE =

Note: No historical examples were found for {tool_name}. Please generate reasonable simulated results based on the tool definition and parameters .

TOOL_SIMULATION_USER_PROMPT = Please generate a simulated return result for the {tool_name} tool for the following parameters :

Parameters: {params_json}

Requirements:

1. Be sure to refer to the real invocation examples; some information may come directly from the examples provided to you. Similar invocation parameters should produce similar simulated results
2. The content must conform to the tool's business logic and real-world scenarios
3. If the result is a list type, generate several reasonable entries
4. Numerical values must be within reasonable ranges
5. Times, dates, etc. must comply with the constraints in the parameters
6. Directly return the result content; do not add any explanations or formatting wrappers

Figure 15: Prompt Template for Tool Simulator

LLM-Judge Prompt Template for Single-Turn Subtask

Task Description

Conduct a **response quality evaluation** for a dialogue that involves tool usage, assessing the model from three core capability dimensions.

Evaluation Objective

Based on the given dialogue content, analyze the model's response along the following three dimensions:

1. **Tool Usage and Planning Capability** – Whether the model fully understands the relationship between the user's request and the available toolset; whether the tool-calling trajectory is clear, reasonable, and accurate; and whether the tool parameters are filled in appropriately and correctly.
2. **Summarization and Extraction Capability** – After obtaining the user's query and the tool function's returned response, whether the model can selectively extract the most critical information (such as required function parameters) based on the available and historical information, while avoiding fabricating facts or inventing data.
3. **Final Answer Description and Presentation Capability** – After completing planning and receiving tool return results, whether the final answer presents the information relevant to the user's needs clearly, accurately, and concisely.

Core Mandatory Constraints

You must treat the following as **primary inspection items throughout all three evaluation dimensions**: **whether tool-call parameters are sourced from real information, whether the parameters are filled in reasonably, whether tool returns are correctly used, and whether the final answer is strictly based on tool returns**.

In the reasoning section, you must explicitly point out:

- **Parameter Authenticity**: Whether key parameters in tool calls (such as center-point latitude / longitude, city / administrative region, keywords, radius, time, stations, etc.) **originate from the dialogue context or tool returns**. If parameters are filled in by the model itself without any source, this is considered a serious issue.
- **Parameter Reasonableness**: Even if parameters have a source, evaluate whether they are appropriate for the current task and user intent. If improper selection of center point or city leads to failed searches or deviated results, this should be penalized.
- **Process Consistency**: Whether the model draws geographic conclusions (distance, direction, within/outside a range, administrative affiliation, etc.) **without searching, locating, or confirming first**, or directly fabricates latitude / longitude or center points. This is a serious deduction.
- **Result Consistency**: Whether factual information in the final answer (distance, range, location relationships, administrative regions, coordinates, routes, etc.) **can be supported item by item by tool returns**. If the tool did not return such information, or the return does not support the conclusion, it is considered hallucination or inconsistency and should be heavily penalized.
- **Exception Handling**: When tool returns are empty, erroneous, missing fields, or clearly unreasonable (e.g., administrative region does not match the center point, coordinates do not correspond to the location), whether the model performs checks, corrections, retries, or follow-up questions. If it instead fabricates conclusions, this is a serious issue.
- **No Tool Invocation**: In tasks where tool usage is expected, if the model provides specific conclusions **without invoking tools at all**, it should be explicitly judged as high-risk hallucination (unless the context already contains all information needed to answer directly).

Evaluation Criteria

1. Tool Usage and Planning Capability

Key Evaluation Points:

- Whether the model understands the mapping between user needs and tool functions , and executes in a user-centric manner without arbitrary deviation .
- Whether the overall tool usage trajectory is reasonable and clear , with explicit planning (including : which tools are needed, the order of usage, where key parameters come from, and how to supplement or ask follow-up questions when parameters are missing).
- Whether all invoked tools are meaningful, avoiding redundant reasoning or tool calls .
- **Parameter and Validation Planning****
 - Whether tool parameters are used reasonably and conform to the tool definition and user intent .
 - Whether there are steps such as "locate first / search first , then conclude" (e.g., obtain coordinates or a center point via tools before performing range or distance searches).
 - Whether there are checks and correction mechanisms when tool returns do not meet expectations (e.g., switching query conditions or asking the user for confirmation when administrative regions do not match; filling missing coordinates before proceeding).

Rating Standards:

- **Very Poor**:** No planning or completely incorrect planning, detached from user needs; or tool parameters are filled unreasonably .
- **Poor**:** Planning has obvious flaws (e.g., unclear or fabricated parameter sources), execution deviates from the goal, lacks exception handling .
- **Average**:** Planning is basically reasonable but has minor logical gaps (e.g., parameter sources not clearly stated or missing validation steps).
- **Good**:** Clear and reasonable planning with only minor shortcomings; parameter sources can be explained and basic validation or follow-up exists .
- **Excellent**:** Complete and precise planning, perfectly executed; parameter sources are explicit , with comprehensive validation and correction mechanisms.

2. Summarization and Extraction Capability

Key Evaluation Points:

- Whether the model can extract core information from the user query and tool return results .
- Whether it focuses on key parameters or points , avoiding irrelevant or redundant content .
- Whether it aligns closely with the established plan .
- Whether it strictly references tool returns and does not fabricate data or facts .
- **Parameter / Field Alignment and Traceability ****
 - Whether key conclusions can be traced to specific tool returns , fields , or entries .
 - Whether field meanings are misinterpreted or misapplied (e.g., treating an administrative region as a center point , or treating search results as a coordinate source).
 - Whether unexpected, empty, or erroneous tool returns are truthfully reflected rather than omitted before giving conclusions .

Rating Standards:

- **Very Poor**:** Hallucinations occur (fabricated parameters, coordinates , distances , administrative regions , or conclusions), or tool errors /empty results /key contradictions are ignored; or definitive conclusions are given without tool support .
- **Poor**:** Key information is omitted or tool fields are misinterpreted ; parameter sources are vague .
- **Average**:** Main information is covered, but unnecessary formatting remains or language organization is loose ; insufficient explanation of parameter sources or evidence chain .
- **Good**:** Accurate extraction with no hallucination , comprehensive coverage; key parameter sources are explained .
- **Excellent**:** While ensuring 100% factual accuracy, the model integrates and analyzes results across multiple tools ; key conclusions are traceable with a complete evidence chain .

When the user question involves travel – related information such as navigation , routing , traffic conditions , arrival time , transportation costs , or weather:

1. The following information types **must come from tools or context****, and must not be estimated based on common knowledge or memory:
 - Precise times (e.g., "estimated arrival at 15:47", "takes 6 minutes");
 - Distances , mileage, congestion length ;
 - Prices or fees (taxi fare , ticket prices , airfare , tolls , etc.);
 - Real-time or date- specific weather, temperature , air quality ;
 - Specific station names, flight numbers, train numbers, etc .
2. If a tool does not return certain data, but the assistant still provides seemingly "helpful" concrete values (e.g., "a taxi costs about 12–15 Yuan", "today is 22 Celsius and sunny"), this should be considered hallucination , not a bonus.

3. Geographic / location-related hard constraints (applicable to POI, administrative region, nearby, range/radius searches, etc.):
- Key parameters such as center-point coordinates, radius, administrative region, and city must come from: explicit user input / existing context / tool returns; otherwise they are considered "fabricated parameters".
 - It is not allowed to assert statements like "X is within Y kilometers of Z" or "Nanchang is within 150 km of Yichun" without prior locating or searching and tool evidence.
 - If searching by administrative region but the center-point coordinates are clearly not within that region (or tool returns indicate inconsistency), the model should be judged as failing reasonableness checks and penalized; if the model retries, corrects, or asks follow-up questions, it may receive additional credit.

3. Final Answer Description and Presentation Capability

Key Evaluation Points:

- Whether the model accurately and directly responds to and completes the user's explicitly stated core request.
- Clarity, logic, and structure of the content.
- Whether information is presented clearly, accurately, and concisely.
- **Credible Expression Based on Tool Results**:
 - When tool results are insufficient to support a conclusion, whether the model explicitly states the limitation and asks the user for necessary information or suggests the next tool invocation, rather than forcing an answer.
 - Whether the response avoids presenting guesses or common knowledge as certain facts, and clearly marks uncertainty.

Rating Standards:

- **Very Poor**: Confusing or incomprehensible description, failure to complete the user request; or provides unfounded definitive conclusions.
- **Poor**: Description lacks clarity or contains obvious redundancy; only partially completes the user request; lacks explanation of tool insufficiency or errors.
- **Average**: Description is understandable but not concise; interaction is limited; partially completes the user request; insufficient credibility boundary prompt.
- **Good**: Clear and concise description, reasonable interaction; fulfills the user request well; indicates the need for more precise information or next steps.
- **Excellent**: Extremely clear, concise, and well-interactive; fully fulfills the user request; proposes additional interaction or immediately executable next actions; strictly bounded by tool evidence.

Response Analysis

Additional Context Information

"""

{CONTEXT_INFO}

"""

User Question Content

"""

{QUESTION_CONTENT}

"""

Available Tools

"""

{INTENDED_TOOL}

"""

Conversation History

"""

{CONVERSATION_HISTORY}

"""

Output Requirements

- Before each rating, you must first provide detailed reasoning (the reasoning must explicitly cover:
 - (1) whether tools should be used / were used;
 - (2) whether parameters have valid sources;
 - (3) whether tool returns support the conclusions;
 - (4) whether there were checks, retries, or follow-up questions when results did not meet expectations).
- Strictly output in the following XML format. Ensure tags are properly closed. The reasoning content must be plain text; do not use any HTML tags such as or
.

```

<response>
<reasoning_planning>
<reasoning>
<!-- Evaluate whether the model's tool invocation trajectory is clear, accurate, and well-planned; focus on
    tool selection, parameter sourcing, and validation / correction when tool returns are abnormal -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</reasoning_planning>
<summarization_extraction>
<reasoning>
<!-- Evaluate whether the model can accurately extract key content from the user question and tool return
    information; strictly check for fabricated latitude / longitude, center points, distances,
    administrative regions; strictly check whether conclusions are consistent with tool evidence -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</summarization_extraction>
<presentation>
<reasoning>
<!-- Evaluate whether the model presents relevant content clearly, accurately, and concisely; when evidence
    is insufficient, whether it clearly states boundaries and guides the user to provide more information
    or take the next step, rather than forcing a definitive answer -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</presentation>
</response>

## Output Example

<response>
<reasoning_planning>
<reasoning>
When handling the user's request for transportation planning from Northeast China to Sanya and
Xishuangbanna, the model exhibited clear logical flaws. First, without querying flights or trains from
Harbin to Xishuangbanna via tools, the model directly provided a specific flight number (YU6852),
flight duration (2 hours), and ticket price (500–800 RMB) in the final answer ...
</reasoning>
<rating>Very Poor</rating>
</reasoning_planning>
<summarization_extraction>
<reasoning>
The model showed serious issues in information extraction and factual accuracy. For transportation to Sanya
, the model partially referenced tool–returned data; however, for Xishuangbanna transportation planning
, it fabricated a non–existent flight number (YU6852, and this airline code does not exist ) without
any supporting tool return ...
</reasoning>
<rating>Very Poor</rating>
</summarization_extraction>
<presentation>
<reasoning>
Although the answer appeared clear and well–structured in format, its core content–especially the
Xishuangbanna section–was built on false information. This kind of "clarity" is therefore misleading.
The model packaged guesses and common knowledge as certain facts, and failed to explicitly state the
limitations caused by not querying transportation information for Xishuangbanna...
</reasoning>
<rating>Poor</rating>
</presentation>
</response>

```

Figure 16: LLM-Judge Prompt Template for Single-Turn Subtask

LLM-Judge Prompt Template for Multi-Turn Subtask

Task Description

Conduct a **response quality evaluation** for a tool-based conversation, assessing the model across **four core capability dimensions**.

Evaluation Objective

Based on the given conversation content, analyze the model's response from the following four dimensions:

1. **Tool Usage and Planning Ability** – Whether the model fully understands the relationship between user needs and the toolset; whether the tool invocation trajectory is clear, reasonable, and accurate; whether the planning of tool calls is correct; and whether tool parameters are filled in appropriately and correctly .
2. **Summarization and Extraction Ability** – After obtaining the user's query and tool function responses, whether the model can selectively extract the most important information (e.g., required function parameters) based on available and historical information, avoiding arbitrary fabrication of facts or data .
3. **Final Answer Description and Presentation Ability** – After completing planning and receiving tool results , whether the final response clearly , accurately , and concisely presents content relevant to the user's needs, and whether it appropriately interacts with or provides feedback to the user (e.g., requesting more precise information or suggesting query-related follow-up questions).
4. **User Interaction and Follow-up Ability** – When information is insufficient , ambiguous, or tool results are abnormal, whether the model can ask necessary and high-value questions with minimal user disruption ; whether it prioritizes inference or tool usage to supplement information ; and whether follow-up questions stay aligned with the user's original intent rather than drifting toward preference-based or irrelevant inquiries .

Core Mandatory Constraints

You must treat the following as **primary inspection items throughout all three evaluation dimensions**:
**whether tool-call parameters are sourced from real information, whether the parameters are filled in reasonably, whether tool returns are correctly used, and whether the final answer is strictly based on tool returns **.

- * **Parameter Authenticity**: Whether key parameters in tool calls (e.g., center coordinates , city / administrative area, keywords, radius , time, stations) originate from the conversation context or tool responses . If parameters are invented by the model without source, this is a serious issue .
- * **Parameter Reasonableness**: Even if parameters have a source, evaluate whether they are suitable for the task and user intent . If inappropriate choices (e.g., wrong center point or city) cause failed or misaligned searches , this should be penalized .
- * **Process Consistency**: Whether the model gives geographic conclusions (distance , direction , within/ outside range , administrative affiliation , etc.) before searching , locating , or confirming information ; or directly fabricates coordinates or center points –this results in severe penalties .
- * **Result Consistency**: Whether factual information in the final answer (distance , range, place relationships , administrative areas, coordinates, routes , etc.) can be fully supported by tool responses . If the tool did not return such information or does not support the conclusion, this is considered hallucination or inconsistency and should be heavily penalized .
- * **Exception Handling**: When tool responses are empty, erroneous, missing fields , or obviously unreasonable (e.g., administrative area does not match center point, coordinates do not match location), whether the model checks, corrects , retries , or follows up. Directly fabricating conclusions in such cases should be heavily penalized .
- * **No Tool Usage**: In tasks where tool usage is expected, if the model provides specific conclusions without calling tools , it should be explicitly judged as high-risk hallucination (unless all necessary information is already provided in context).
- * **Minimal-Disruption Interaction Principle**: If missing information can be inferred from context or obtained via tools , but the model instead asks the user, this should be penalized . If follow-up questions deviate from the user's original goal or needs, this should also be penalized .

Evaluation Criteria

1. Tool Usage and Planning Ability

Evaluation Focus:

- * Whether the model understands the alignment between user needs and tool capabilities , and remains user-centered during execution without unnecessary deviation .
- * Whether the overall tool usage trajectory is reasonable and clear , including a clear plan (what tools are

needed, in what order, where key parameters come from, and how to handle missing information via supplementation, follow-up, or retry).

- * Whether all invoked tools are meaningful, avoiding redundant reasoning or calls .
- * **Parameter and Validation Planning**:**

- * Whether tool parameters are reasonable and consistent with tool definitions and user intent .
- * Whether there is a "locate/search before concluding" step (e.g., obtaining coordinates or center points before range or distance queries).
- * Whether there is validation and correction logic when tool results do not meet expectations (e.g., mismatched administrative areas leading to revised queries or user confirmation).

Rating Scale:**

- * Very Poor: No planning or completely incorrect planning, disconnected from user needs; or unreasonable tool parameters .
- * Poor: Clear planning flaws (e.g., unclear or fabricated parameter sources), deviation from goals, lack of exception handling .
- * Average: Generally reasonable planning with minor logical gaps (e.g., unclear parameter sources or missing validation steps).
- * Good: Clear and reasonable planning with only minor issues ; parameter sources explained with basic validation or follow-up .
- * Excellent : Complete and precise planning, perfect execution; parameter sources explicit with comprehensive validation and correction mechanisms.

2. Summarization and Extraction Ability

Evaluation Focus:**

- * Whether the model extracts core information from user queries and tool responses .
- * Whether it focuses on key parameters or points and avoids irrelevant content .
- * Whether it aligns with the established plan .
- * Whether it strictly references tool responses without fabricating data or facts .
- * **Parameter/Field Alignment and Traceability **:**

- * Whether key conclusions can be traced to specific tool outputs or fields .
- * Whether fields are misinterpreted or mismatched (e.g., treating administrative areas as center points , or search results as coordinate sources).
- * Whether tool outputs that are empty, erroneous, or unexpected are honestly reflected rather than omitted before drawing conclusions .

Rating Scale:**

- * Very Poor: Hallucinations (fabricated parameters, coordinates , distances , administrative areas , or conclusions), or ignoring tool errors /empty results while giving definitive answers .
- * Poor: Missing key information or misinterpreting tool fields ; vague parameter sourcing .
- * Average: Covers main information but includes unnecessary formatting or loose organization ; insufficient explanation of parameter evidence .
- * Good: Accurate extraction with no hallucination ; comprehensive coverage; clear explanation of parameter sources .
- * Excellent : While maintaining 100% factual accuracy, integrates and analyzes results across multiple tools ; conclusions are fully traceable with complete evidence chains .

When user questions involve navigation , routing , traffic , arrival times , transportation costs , weather , or travel – related information :

1. The following information types must come from tools or context and must not be estimated from common knowledge or memory:
 - * Precise times (e.g., "estimated arrival at 15:47", "takes 6 minutes");
 - * Distances , mileage, congestion lengths ;
 - * Prices or costs (taxi fares, tickets , airfares , tolls , etc .);
 - * Real-time or date-specific weather, temperature, air quality ;
 - * Specific station names, flight numbers, train numbers, etc .
2. If tools do not return certain data, but the assistant provides seemingly "helpful" specific numbers (e.g., "taxi costs about 12–15 Yuan", "today is sunny, 22 Celsius"), this should be treated as hallucination , not a bonus.

3. Geographic/location hard constraints (applicable to POI, administrative areas, nearby/radius searches):

- * Center coordinates, radius, administrative areas, cities must come from explicit user input, existing context, or tool responses; otherwise, they are considered fabricated parameters.
- * It is not allowed to assert "within/outside X km" or similar claims without tool evidence.
- * If searching by administrative area but the center point clearly does not lie within that area (or tool results show inconsistency), failure to validate should be penalized; retries, corrections, or follow-ups should be rewarded.

3. Final Answer Description and Presentation Ability

Evaluation Focus:

- * Whether the response accurately and directly fulfills the user's explicit core request.
- * Clarity, logic, and structure of the presentation.
- * Conciseness and precision.

Credible Expression Based on Tool Results:

- * When tool results are insufficient to support conclusions, whether limitations are clearly stated and necessary information or next steps are requested, rather than forcing an answer.
- * Whether guesses or common knowledge are clearly marked as uncertain instead of presented as facts.

Rating Scale:

- * Very Poor: Confusing, incomprehensible, or fails to meet user needs; or provides unsupported definitive conclusions.
- * Poor: Unclear or redundant descriptions; partial task completion; insufficient explanation of tool limitations or errors.
- * Average: Understandable but not concise; limited interaction; partial fulfillment; insufficient boundary clarification.
- * Good: Clear, concise, and well-structured; reasonable interaction; effectively fulfills user needs; suggests next steps.
- * Excellent: Extremely clear and concise with effective interaction; fully fulfills user needs; proposes actionable next steps while strictly respecting tool evidence boundaries.

4. User Interaction and Follow-up Ability

Evaluation Focus (aligned with the first three dimensions but focused on "asking the right questions, asking fewer questions, and asking valuable questions"):

- * Necessity: Questions are asked only when key information is missing and cannot be supplemented via tools or context.
- * Minimal Disruption: Fewest questions possible; merging multiple gaps into one high-information question; avoiding chained follow-ups.
- * ** Substitutability Check**: Whether tools could have been used instead of asking the user; unnecessary questions are penalized.
- * Question Quality: Specific, actionable, targeting key parameters (location, time, range, object ID), not vague questions like "What do you want?".
- * Intent Alignment: Follow-ups stay aligned with the original task; unnecessary preference questions are penalized.
- * Tool-Based Follow-ups: When tool results are empty, conflicting, or ambiguous, whether clarifications reference those results (e.g., providing candidates for selection).
- * Interaction Closure: After follow-up, whether the next step and how the information will be used is clearly stated; avoiding unused questions.

Rating Scale:

- * Very Poor: Excessive unnecessary questions; asking users for information obtainable via tools; off-topic questions; no execution closure.
- * Poor: Clearly unnecessary or off-intent questions; overly broad; multiple unmerged follow-ups.
- * Average: Generally reasonable but slightly excessive or unfocused; insufficient explanation of purpose.
- * Good: Questions asked only when necessary; clear and focused; tool-first verification; follow-ups based on tool results.
- * Excellent: Mature interaction strategy: tool-first supplementation → only ask irreducible questions; ask once for key information; provide options to reduce user input; clear execution loop with minimal disruption.

Response Analysis

```

### Additional Context Information

"""
{CONTEXT_INFO}
"""

### User Question Content

"""
{QUESTION_CONTENT}
"""

### Available Tools

"""
{INTENDED_TOOL}
"""

### Conversation History

"""
{CONVERSATION_HISTORY}
"""

## Output Requirements

* Before each rating , provide detailed reasoning that explicitly covers:
(1) whether tools should have been used and whether they were used;
(2) whether parameters have valid sources ;
(3) whether tool results support the conclusions ;
(4) whether unexpected results were checked, retried , or followed up;
(5) whether follow-ups were necessary , minimally disruptive , tool– substitutable , and aligned with user intent .
* Strictly output in the following XML format, ensuring proper tag closure . The reasoning content must be plain text ; do not use any HTML tags such as <b> or <br>.

<reasoning>
<!-- Evaluate whether the model's tool invocation trajectory is clear , accurate , and well–planned; focus on tool selection , parameter sources , and validation and correction when tool returns are abnormal -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</reasoning_planning>
<summarization_extraction>
<reasoning>
<!-- Evaluate whether the model can accurately extract key content based on the user question and tool return information ; strictly check for fabricated latitude /longitude , center points , distances , administrative regions , etc .; strictly check whether conclusions are consistent with tool evidence -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</summarization_extraction>
<presentation>
<reasoning>
<!-- Evaluate whether the model presents relevant content clearly , accurately , and concisely ; when evidence is insufficient , whether it clearly states boundaries and guides the user to provide additional information or take the next step , rather than forcing a definitive conclusion -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</presentation>
<user_interaction>
<reasoning>
<!-- Evaluate whether follow-up questions / interaction are necessary and minimally intrusive : information obtainable via tools or context should not be asked again; whether questions are consolidated into high-information–density prompts focusing on key parameters; whether follow-ups align with user intent and are based on tool returns ; whether an action loop is formed after follow-up -->
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>

```

```

</ user_interaction >
</response>

## Output Example

<response>
<reasoning_planning>
<reasoning>
When handling the user's request for transportation planning from Northeast China to Sanya and Xishuangbanna, the model exhibited obvious logical flaws. First, without querying flight or train information from Harbin to Xishuangbanna through tools, the model directly provided a specific flight number (YU6852), flight duration (2 hours), and ticket price (500–800 RMB) in the final answer ...
</reasoning>
<rating>Very Poor</rating>
</reasoning_planning>
<summarization_extraction>
<reasoning>
The model demonstrated serious issues in information extraction and factual accuracy. For transportation to Sanya, the model did reference part of the tool–returned data; however, for the transportation plan to Xishuangbanna, the model fabricated a fictitious flight number (YU6852, and this airline code does not exist) without any supporting tool return ...
</reasoning>
<rating>Very Poor</rating>
</summarization_extraction>
<presentation>
<reasoning>
Although the answer's format appears clear and structured, its core content—especially the Xishuangbanna section—is built on false information. This kind of "clarity" is therefore misleading. The model packaged guesses and common knowledge as certain facts, and failed to explicitly state the limitations caused by not querying transportation information for Xishuangbanna...
</reasoning>
<rating>Poor</rating>
</presentation>
<user_interaction >
<reasoning>
When critical information was missing (no query of Xishuangbanna transportation), the model neither chose to ask the user to clarify the specific departure city (although the context suggested Heilongjiang, the exact city was not confirmed), nor informed the user of the query failure. Instead, it opted for the worst possible approach: fabricating conclusions outright ...
</reasoning>
<rating>Very Poor</rating>
</user_interaction >
</response>

```

Figure 17: LLM-Judge Prompt Template for Multi-Turn Subtask

Prompt Template for Meta-Judge

Task Description

Conduct a **Meta-Evaluation** of an evaluation result for a conversation – that is, evaluate the **quality and credibility of the evaluation itself**, rather than re-evaluating the original conversation.

Evaluation Objective

Based on the original conversation trace and the output of the first-round evaluation (including per-dimension ratings and rationales), comprehensively judge whether that evaluation is reliable in the following aspects:

1. **Scoring Accuracy**:

Whether the ratings for each dimension genuinely reflect the model's actual performance in the conversation; whether there is any obvious overestimation or underestimation.

2. **Reasoning and Evidence Chain**:
Whether the evaluation rationale is logically clear, traceable, and grounded in key evidence (conversation turns / tool calls / tool outputs), rather than vague or generic judgments.
3. **Consistency and Strictness of Standards**:
Whether the evaluation strictly enforces predefined hard constraints and dimension standards (especially parameter authenticity, result consistency, and exception handling), and whether it is overly lenient or overly harsh.
4. **Coverage and Completeness**:
Whether the evaluation checks all critical risk points and strengths, and whether it omits serious issues or important positive aspects.
5. **Cross-Dimension Coherence**:
Whether ratings across different dimensions are mutually consistent and supportive; if contradictions exist (e.g., reasoning identifies severe hallucination but the rating is still "good" or "excellent"), they must be explicitly pointed out.

Original Conversation Information

Context Information

"""

{CONTEXT_INFO}

"""

User Question

"""

{QUESTION_CONTENT}

"""

Tool Definition

"""

{INTENDED_TOOL}

"""

Conversation History

"""

{CONVERSATION_HISTORY}

"""

First -Round Evaluation Result

Evaluation Dimensions and Ratings

{EVALUATION_SCORES}

Per-Dimension Rationales / Reasoning

{EVALUATION_REASONING}

Meta-Evaluation Checklist (Must Be Examined Item by Item)

Please evaluate the quality of the first -round evaluation from the following perspectives, and explicitly provide evidence in your reasoning:

A. Reasonableness of the Scores

- * Whether the ratings for each dimension are consistent with the factual conversation record (especially tool call traces, parameter sources, tool outputs, and the final answer).
- * Whether there is obvious overestimation or underestimation; if so, explain why the score should be higher or lower, with evidence.
- * Whether the dimensions are internally consistent: whether the same issue is heavily penalized in one dimension but ignored in another.

B. Adequacy of Reasoning (Evidence Chain)

- * Whether the rationale is concrete: does it quote key sentences from the dialogue, tool call parameters, or tool output fields to support its judgments.
- * Whether it distinguishes between verifiable facts and speculative judgments, avoiding subjective or generic commentary.
- * Whether key errors are clearly attributed (e.g., fabricated parameters, failure to use tools, misreading fields, ignoring empty results).
- * Whether important issues are omitted.

C. Strict Enforcement of Standards (Hard Constraints First)

Focus on whether the first –round evaluation properly enforced the following hard constraints in its scoring :

- * **Parameter Authenticity:**
Whether it checked that key parameters came from the context or tool outputs; if parameters lacked provenance, whether this was severely penalized.
- * **Result Consistency:**
Whether the final answer was strictly supported, item by item, by tool outputs; if tools did not return results or did not support the answer, whether this was judged as hallucination.
- * **Process Consistency:**
Whether conclusions (e.g., geographic conclusions) were made without retrieval or localization, and whether the evaluation identified and penalized this.
- * **Exception Handling:**
When tools returned empty results, errors, or contradictions, whether the evaluation required retries, corrections, or follow-up questions, and scored accordingly.
- * If the evaluation glossed over or failed to mention these issues, it should be considered non-strict.

D. Coverage and Completeness

- * Whether all critical stages were covered: requirement understanding → planning/tools → parameter provenance → result usage → final presentation → interaction /follow-up (if applicable).
- * Whether serious risk points were omitted (e.g., fabricated coordinates / distances / costs /times, ignoring empty tool results).
- * Whether the model's strong points were omitted (e.g., reasonable retry strategies, clear evidence-chain explanations, appropriate boundary disclaimers).

E. Re-evaluation Consistency (Counterfactual Check)

- * If you re–evaluated using the same standards, would you give the **same overall level** of judgment?
- * If not, identify the most critical points of deviation (no need to redo the full scoring, but explain the reasons for the difference).

Output Requirements

- * Output a single overall rating : **Very Poor / Poor / Average / Good / Excellent** (do not output numbers or scores).
- * The reasoning must explicitly state whether the first –round evaluation meets the standards in the four areas of **parameter authenticity**, **result consistency**, **exception handling**, and **evidence–chain citation**, and whether there are cross–dimension contradictions or omissions.
- * Strictly output in the following XML format. Ensure correct tag usage. The `reasoning` content must be plain text. Do not use any HTML tags such as `` or `
`:

```
```xml
<meta_evaluation>
<reasoning>
<!-- Provide a detailed analysis of the quality of this evaluation, covering:
1. Scoring accuracy and overestimation /underestimation (with evidence)
2. Sufficiency of reasoning and evidence chain (citing dialogue/tool parameters/tool outputs)
3. Consistency and strictness of standard enforcement (whether hard constraints were applied)
4. Coverage and omitted points
5. Overall conclusion: whether your re–evaluation would yield the same level, and why -->
```

```
</reasoning>
<rating><!-- Rating: Very Poor, Poor, Average, Good, Excellent --></rating>
</meta_evaluation>
```

Figure 18: Prompt Template for Meta LLM Judge