# COMPASS: A MULTI-TURN BENCHMARK FOR TOOL-MEDIATED PLANNING & PREFERENCE OPTIMIZATION

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#### **ABSTRACT**

Real-world LLM agents must master strategic tool orchestration and user preference optimization through multi-turn interactions to assist users with complex planning tasks. We introduce COMPASS (Constrained Optimization through Multi-turn Planning and Strategic Solutions), a benchmark that evaluates agents on realistic travel planning scenarios. We cast travel planning as a constrained preference optimization problem, where agents must satisfy hard constraints while simultaneously optimizing soft user preferences. To support this, we build a realistic travel database covering transportation, accommodation and ticketing for 20 U.S. National Parks and a comprehensive tool ecosystem that mirrors commercial booking platforms. Evaluating state-of-the-art models, we uncover two critical gaps: (i) an accept**able-optimal gap**, where agents reliably meet constraints but fail to optimize preferences, and (ii) a plan-coordination gap, where performance collapses on multi-services (flight, hotel) coordination tasks, especially for open-source models. By grounding reasoning and planning in a practical, user-facing domain, COM-PASS offers a benchmark that directly measures an agent's ability to optimize user preferences in realistic tasks, bridging theoretical advances with real-world impact.

## 1 Introduction

As Large Language Models (LLMs) move toward real-world deployment, their role is increasingly to assist users with everyday tasks that blend strict requirements with soft preferences. A natural way to formalize such interactions is through the lens of *constrained preference optimization*: agents must satisfy hard constraints (e.g., travel dates, budget limits, accessibility requirements) while simultaneously optimizing soft user preferences (e.g., cheapest options or wish-lists). Within this framework, tool-mediated problem solving is the mechanism that enables agents to reason strategically and invoke external resources. By iteratively refining their plans, agents can build coherent solutions that align with user preferences. This dual capacity for constraint satisfaction and preference optimization is therefore a core requirement for LLM agents to be genuinely useful in practice. <sup>1</sup>

Current benchmarks, however, fall short of evaluating these core capabilities. Most planning benchmarks reduce tasks to single-turn constraint satisfaction (Xie et al., 2024; Kohli et al., 2024), where finding any feasible solution is sufficient. Yet, preference optimization requires *qualitatively* different skills: rather than stopping at the first valid solution, agents must compare alternatives and select the one that best aligns with user preferences. Likewise, existing tool-use benchmarks focus narrowly on whether agents call the correct tool with valid parameters (Zhong et al., 2025; Yao et al., 2024), without testing how agents adapt to multi-turn interactions, where users naturally add new requirements and provide feedbacks (Wang et al., 2023; Laban et al., 2025). Finally, most benchmarks rely

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<sup>&</sup>lt;sup>1</sup>Data and code is available at: https://github.com/sunnytqin/compass.git

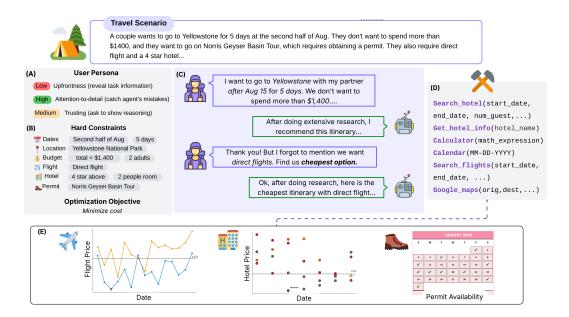


Figure 1: *COMPASS* benchmark framework. The environment integrates three key components for realistic evaluation of agentic capabilities in travel planning. (A) A modular LLM-based user simulator enables controllable multi-turn interactions, progressive constraint revelation, and diverse user personas. (B) We formalize travel planning as *constrained preference optimization*, where agents must satisfy hard constraints (feasible solutions) while optimizing soft user objectives (e.g., minimizing cost, maximizing amenities). (C) Agents interact with realistic travel databases (E) using a comprehensive tool ecosystem (D), requiring iterative planning and refinement across conversation turns to construct optimal itineraries.

on simplified mock databases. However, database realism directly shapes task difficulty—authentic evaluation requires rich, complex environments to meaningfully assess agent capabilities.

To address these gaps, we introduce *COMPASS*, a benchmark that instantiates constrained preference optimization in the setting of realistic travel planning. In *COMPASS*, agents must satisfy hard constraints such as budget, occupancy, and scheduling while simultaneously optimizing soft preferences such as minimizing cost or maximizing wish-list amenities (Fig.1 B). To support this evaluation, we construct a full environment consisting of (i) a modular LLM-based user simulator for controllable multi-turn interactions (Fig.1 A, C), (ii) a realistic database of hotels, flights, and activity permits derived from commercial sources (Fig.1 E), and (iii) a tool ecosystem that mirrors booking platforms, enabling agents to search, filter, and combine information (Fig.1 D). Tasks are organized along two axes: **task types**, which define whether optimization is based on a single numerical metric or maximizing a checklist of desired features, and **task levels**, which range from hotel-only scenarios to full itineraries involving flights and permits. Together, these components provide a rigorous yet practical benchmark for assessing whether LLM agents can go beyond constraint satisfaction to deliver optimal, user-preference aligned solutions.

Through extensive evaluation of state-of-the-art models, we uncover two critical findings that reveal fundamental limitations in current agentic capabilities. First, we observe a significant **acceptable-optimal gap** (Fig. 2): while all models achieve high acceptable rates (constraint satisfaction), they show substantially lower optimal rates (preference optimization), indicating agents settle for feasible solutions rather than optimizing user preferences even when preference objectives are clearly specified. Second, we identify a substantial **plan-coordination gap** (Fig. 4 A): performance degrades sharply once tasks require comprehensive planning across services (hotel, flight). At these levels, agents must align hotels, flights, and permits under temporal and budget constraints, and orchestrate multiple tool calls to maintain plan (itinerary) consistency. While closed-source models show gradual decline, open-source models struggle dramatically, highlighting the difficulty of coordination in realistic travel scenarios. Together, *COMPASS* serves as a rigorous benchmark for diagnosing the core challenges of constrained preference optimization and guiding the development of user-aligned AI agents.

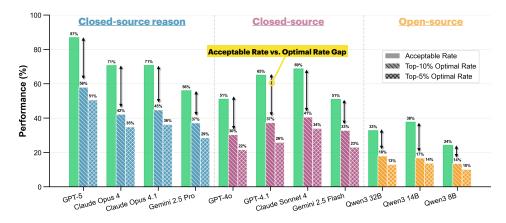


Figure 2: *COMPASS* benchmark main results. Acceptable rate measures feasibility (satisfying all hard constraints). Optimal rate measures preference optimization (achieving utility within the top 10% of feasible solutions). All models show a  $\sim 20\%$  gap between high acceptable rates and low optimal rates, revealing that agents settle for feasible solutions rather than optimizing preferences. Encouragingly, open-source models like Qwen3-32B achieve non-trivial performance, demonstrating emerging agentic capabilities.

## 2 RELATED WORK

**Tool-Use and Planning Benchmarks** Recent benchmarks have evaluated language model agents across tool-use and planning capabilities, though typically in isolation. Tool-use benchmarks like Tau-Bench (Yao et al., 2024; Barres et al., 2025) provide comprehensive API libraries but focus primarily on instruction-following in a online customer service setting. Patil et al. (2025) includes a wider tool library but user multi-turn is based on predetermined conversation trajectories, while others (Wang et al., 2023) evaluate coding scenarios with oracle-like users. Planning benchmarks have emerged to assess constraint satisfaction and optimization: Zheng et al. (2024) evaluates natural language planning tasks while eliminating tool-use complexity, and Kohli et al. (2024) presents flight booking scenarios in multiple-choice format without interactive tool integration. More comprehensive planning evaluation includes multi-day travel planning with hard constraints (Xie et al., 2024), though without the multi-turn preference revelation that characterizes real user interactions. Our work is the first to combine tool-calling, planning, and preference optimization in a multi-turn setting—a combination essential for agents deployed in real-world scenarios where users progressively reveal constraints while agents must dynamically adapt their search and optimization strategies. Concurrent work Qian et al. (2025) also explores user preference optimization in a planning setting but with a stronger focus on preference elicitation.

Multi-Turn Interactions and Task-Oriented Dialogue Assessing agent capabilities in multi-turn settings is crucial for real-world deployment, as users naturally reveal requirements incrementally rather than specifying complete constraints upfront (Laban et al., 2025). Traditional task-oriented dialogue systems (Budzianowski et al., 2018; Rastogi et al., 2019) provide foundational insights: multi-turn interactions occur because users reveal new requirements, request information, and adapt goals when constraints cannot be satisfied. However, these systems typically lack the tool integration and utility optimization challenges present in modern agent evaluation. Recent work on multi-turn agent evaluation includes simple tasks like city guessing (Abdulhai et al., 2023) and preference learning through turn-based rewards (Wan et al., 2025), but lacks the complexity of realistic planning scenarios. Drawing inspiration from task-oriented dialogue research, our user simulator design achieves diverse interaction dynamics through progressive constraint revelation, mimicking how real users gradually specify preferences while maintaining the authentic conversational patterns observed in human-to-human planning dialogues. We provide an extensive related work in App. B.

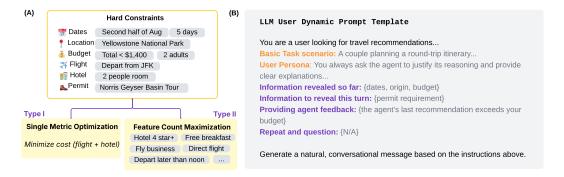


Figure 3: **Examples of task types and dynamic user simulator prompt.** (A) Two task types are defined based on the soft preference-optimization objective. Each task type includes hard constraints but differs in optimization objective (Sec. 3.2). (B) The dynamic LLM user simulator prompt (Sec. 3.4) controls multi-turn conversation dynamics. The system prompt consists of static instructions (orange), fixed for each conversation, and dynamic fields (purple), which are updated at every turn based on the conversation state.

## 3 COMPASS BENCHMARK

#### 3.1 TRAVEL PLANNING AS CONSTRAINED PREFERENCE OPTIMIZATION

A central challenge for real-world agents is to not only satisfy user requirements but also optimize for user satisfaction. To capture this duality, we formulate travel planning as a constrained preference optimization problem, where **hard constraints** define the feasible set of solutions and **soft preferences** rank those solutions by user preference. Hard constraints represent non-negotiable requirements—budget limits ("total cost under \$3000"), occupancy needs ("6 people, max 2 per room"), or logistical requirements ("permit required for Extended Cave Tour"). Within this feasible set, user preference objectives capture user priorities such as minimizing cost, maximizing amenities. This separation between feasibility and desirability provides a principled way to evaluate whether agents can go beyond finding one valid solution to finding the best solution based on user requests.

#### 3.2 TASK DESIGN

**Task Types** Real users have different ways of defining the "best" travel itinerary. To balance realism with clarity of evaluation, we design two complementary soft preference types that capture distinct optimization behaviors.

- Single Metric Optimization Task. The user specifies one numerical objective, and the agent optimizes along that single axis. For example: "find me the cheapest trip" (minimize cost) or "book the highest-rated hotel available" (maximize review score). Here, success means identifying the extreme value on a clearly defined metric.
- Feature Count Maximization Task. The user provides a wish list of desirable attributes, such as "hotel with spa, pool, and in-room kitchen; flight with WiFi and direct routing." These are not strict requirements—an itinerary that satisfies three out of five features is preferable to one that satisfies only one. The agent must therefore find the option that maximizes the total number of satisfied features, reflecting the realistic setting where users treat many preferences as flexible "nice-to-haves."

In both task types, each task *always* includes a set of hard constraints. Figure 3 (A) shows examples of each task type. The optimization objectives are explicitly designed to be quantitatively measurable, ensuring that each task is well-specified from a benchmarking perspective. At the same time, when combined with hard constraints, these optimization objectives yield rich and realistic user behaviors. For instance, in a single-metric optimization task, a user may aim for the cheapest option (*optimization objective*) while still requiring a hotel rated at least three stars (*hard constraint*). In a feature-count maximization task, a user may prefer business-class flights and luxury hotels (*optimization objective*) but restrict total spending to under \$2,000 (*hard constraint*). This combination balances benchmark clarity and comparability with realism and diversity in user preferences.

Table 1: *COMPASS* benchmark characteristics. *Left:* Task distribution (Sec. 3.2) across three complexity levels, and split between the two optimization types, and data scale covering geographic coverage, inventory size, and benchmark components. *Right:* Complete tool suite (Sec. 3.3) organized by category, listing 18 APIs for navigation, search, validation, and utility functions.

Category	Item	Count
	Level I (Hotel only)	142
Task Levels	Level II (Hotel, Flight)	69
	Level III (Hotel, Flight, Permit)	70
	Total Tasks	281
Task Types	Single Metric Optimization	154
task Types	Feature Count Maximization	127
	National Parks (Destinations)	20
	Airports	21
Database Scale	Hotel Room Bookable Offers	100,000+
	Flight Bookable Offers	67,000+
	Trail Permits	50

Tool Category	Tool Name
Hotel	search_hotel get_hotel_details get_room_details search_location_name
Flight	<pre>search_airports search_flights get_flight_details get_airport_location</pre>
Permit	list_permits search_permit_availability
Utility	notebook calendar calculator calculate_driving_distance validate_hotel(_flight_permit)_id

**Task Levels** For each task type, we also vary the difficulty of tasks. We design three levels of increasing complexity, enabling systematic evaluation of agents' planning and reasoning capabilities.

- Level I (Hotel Only): Agents must navigate room configurations and pricing structures under constraints such as budget, occupancy, and amenities.
- Level II (Hotel + Flight): Agents plan complete trips with both accommodations and transportation. This requires temporal reasoning to align departure dates with hotel availability while distributing the budget across both services.
- Level III (Hotel + Flight + Permits): Agents incorporate reservations for guided tours or hiking experiences with limited availability. Permits introduce additional temporal constraints: permit availability can dictate travel dates, which in turn determine feasible hotel and flight options.

This progression serves three evaluation purposes: (1) *Practical relevance* — comprehensive planning across services (hotel, flights) reflects real deployment scenarios, where an ideal agent should produce full itineraries that optimize user experience. (2) *Sequential reasoning* — higher levels require chaining constraints across domains, such as permit availability driving hotel selection, which then constraints flight booking. (3) *Tool orchestration complexity* — agents must coordinate multiple APIs and handle compound constraints (e.g., "hotel within 3 hours' drive of airport").

We design tasks using 36 diverse user templates (e.g., budget backpacker, family with children, wedding planner), each specifying a travel scenario with associated hard constraints and soft preferences. From these templates, we generate 240 total tasks across the three complexity levels by sampling parameters such as travel dates, destinations, and budget ranges (See Tab. 1 for task breakdown). We further vary task difficulty along multiple axes: number of constraints, temporal complexity (flexible vs. fixed dates), spatial complexity (single vs. multiple destinations), and required tool interaction depth. App. D.1 provides a detailed breakdown of all tasks and concrete examples.

## 3.3 Database Construction & Tools Design

The complexity of the underlying data directly shapes the difficulty and realism of an optimization benchmark. Oversimplified databases fail to reflect real-world challenges, while overly complex ones reduce practical relevance. To balance these factors, *COMPASS* uses real travel data obtained through RapidAPI,<sup>2</sup> constructing clean SQL databases from actual booking information. Our dataset covers 20 U.S. National Parks, each with 20 hotels offering diverse room types, prices, amenities, and policies. We also include flight data from four major airlines with varied routing options and booking classes. Permit data is mocked, but modeled after real high-demand permits (e.g., the Yosemite Half Dome hike <sup>3</sup>), ensuring scenarios remain authentic.

COMPASS also provides a comprehensive tool suite that both mirrors commercial booking platforms and tests agents' reasoning. Core search functions (search\_hotel,search\_flights) are complemented by

<sup>&</sup>lt;sup>2</sup>https://rapidapi.com/DataCrawler/api/booking-com15

<sup>&</sup>lt;sup>3</sup>https://www.nps.gov/yose/planyourvisit/hdpermits.htm

utility tools (calculator, notebook) that support multi-step problem solving. Our search tools accept rich filters (e.g., price ranges, amenity requirements, routing preferences), providing agents the optionality to strategically conduct search. A full list of tools is shown in Tab. 1 (*right*) and detailed in App. D.2.

#### 3.4 USER SIMULATOR DESIGN

We use GPT-5 as the backbone of our user simulator. Unlike prior benchmarks (Yao et al., 2024; Lu et al., 2024) that rely on a single static prompt for the entire dialogue, our simulator employs **dynamic prompting**—adjusting instructions both across different users and within each conversation turn. Compared to existing works (Yao et al., 2024; Lu et al., 2024) that use static user prompt designs, our simulator enables fine-grained control over user behavior. Fig. 3 (B) shows a demonstration of the dynamic prompting template and App. D.4 lists the verbatim prompt template. We control two within-conversation dynamics: (1) **Progressive constraint revelation**, where users disclose task information incrementally rather than upfront, and (2) **Trust and communication patterns**, where users vary in whether they accept recommendations immediately or demand explicit reasoning. We also introduce two axes of persona diversity: (3) **Constraint-checking reliability**, where users differ in how consistently they detect and correct agent mistakes, and (4) **Conversation style**, where personas range from concise and pragmatic to repetitive, emotional, or insistent.

At each dialogue turn, the dynamic sections of the user prompt are updated to reflect the current conversation state—what task information has been revealed, what remains to be revealed, the user's feedback on the agent's last response, and whether the user should trigger questioning behaviors (e.g., asking the agent to double-check a recommendation). Static sections, by contrast, encode user persona and task-level context. Together, this dynamic prompting framework produces diverse yet controlled conversations, allowing systematic evaluation of how agents adapt to different users.

#### 3.5 EVALUATION METRIC DESIGN

**Ground Truth Generation** To evaluate agents reliably, we construct ground truth solutions for every task through exhaustive search. We begin by enumerating all candidate hotels, flights (Levels II & III), and permits (Level III), applying single-domain filters (e.g., direct flights, 4-star hotels). We then generate all possible cross-domain combinations and eliminate any that violate hard constraints such as budget limits or airport–hotel driving times. The remaining set defines the complete feasible space.

For both task types (Sec 3.2), we compute an exact *utility score*. In single-metric optimization tasks, the score is the numerical value of the target metric (e.g., total price, average review score). In feature-count maximization tasks, the score is the number of desired features satisfied. This exhaustive approach guarantees correctness, since every feasible solution is enumerated and scored. We further validate ground truth quality by discarding tasks with too few feasible solutions or with too many tied optima ( $\geq 20\%$  of the feasible set), ensuring each task poses a meaningful optimization challenge.

**Evaluation Metrics** From this solution library, we evaluate agents along two dimensions. For *constraint satisfaction*, we check whether at least one agent-recommended itinerary belongs to the feasible set, reporting the acceptable rate. For *preference optimization*, we assess how close the agent's best recommendation comes to the top-performing feasible solutions, reporting the optimality rate. We provide formal definition below:

Acceptable Rate: Fraction of tasks agent's recommendation satisfies user's hard constraints.

**Optimality Rate**: Fraction of tasks where agent's recommendation falls within the top i-th percentile.

## 4 EXPERIMENT

## 4.1 MAIN RESULTS

We evaluate *COMPASS* on a range of frontier closed-source models, including both reasoning-enabled and standard versions of GPT OpenAI et al. (2023); OpenAI (2025), Claude Anthropic (2025), and Gemini(Comanici et al., 2025), as well as the frontier open-source model Qwen3 Yang et al. (2025). All models support native tool calling, and we pass the tool schema directly to the model interface.

Table 2: **Human evaluation of LLM user simulator quality.** Left: Scoring rubrics used by annotators for clarity and contextual appropriateness. Right: Human evaluation results on 198 user responses. Rubric scores are reported as mean  $\pm$  standard deviation, as well as median, and quantile cut-offs. Error rates are reported as percentages of responses exhibiting each error type.

Clarity
5: Crystal clear communication of requirements and goals
4: Clear with no confusion about the task
3: Mostly clear but some minor ambiguity that won't affect results
2: Unclear communication that could lead agent to make mistakes
1: So unclear the agent will likely fail the task
Contextual Appropriateness
Contextual Appropriateness  5: As good as you would write or better
** *
5: As good as you would write or better
5: As good as you would write or better 4: Good without any obvious issues

Metric	Result
Quality Scores (1–5) ↑	
Clarity	$3.9 \pm 1.2$
Median	4.0
Percentiles (25/50/75/90/95)	3/4/5/5/5
Contextual appropriateness	$3.7 \pm 1.1$
Median	4.0
Percentiles (25/50/75/90/95)	3/4/5/5/5
Error Rates	
Factual hallucination	6.1%
Information revelation failures	4.0%
Constraint checking failures	0.5%

To standardize outputs, agents are required to return a JSON object listing all "package\_ids", which uniquely identifies a booking configuration, in the required fields ("flights"/"hotel"/"permit"), or leave them empty if not applicable. We evaluate each agent on the final itinerary it produces. Fig. 2 reports aggregate performance. App. E provides inference details for each model, App. A.1 reports a detailed breakdown table of model performances, and App. A.2 confirms benchmark stability with small error bars across repeated runs.

We find a significant gap between constrained-preference satisfaction and preference optimization. All models achieve high acceptable rates, showing they can interpret constraints and return feasible solutions. However, their 5% and 10% optimality rates are substantially lower, revealing that agents often settle for feasible but suboptimal solutions even when objectives are simple and explicitly stated. Reasoning models outperform non-reasoning counterparts, and open-source Qwen3-32B (reasoning enabled) reaches close to 20% optimality rate—comparable to some closed-source systems such as GPT-4o. This suggests that strong agentic capabilities are emerging in open-source models. Nonetheless, GPT-5 shows superior performance across both dimensions, outperforming all other models.

## 4.2 VALIDATING LLM USER SIMULATOR QUALITY

To ensure our LLM user simulator produces realistic and reliable interactions, we randomly sample 45 full conversations spanning diverse personas, task types, and agent interactions. From these, we extract *198* individual user responses for human evaluation by an independent expert annotation service, covering the full range of scenarios in the *COMPASS* benchmark.

Annotators assess each response along two dimensions. (1) **Rubric-based quality assessment:** responses are scored on two axes. The *clarity* axis measures whether user messages are expressed in a way that avoids misleading the agent or causing task failure; a score below 3 (on a 1–5 scale) indicates that the simulator may have provided confusing or incorrect task information. The *contextual appropriateness* axis evaluates whether responses flow naturally within a travel-planning dialogue. (2) **Detailed error detection:** since behaviors such as constraint revelation and trust patterns are explicitly controlled (Sec. 3.4), annotators tag whether the simulator follows its prompts correctly without hallucination or deviation. The scoring rubric appears in Tab. 2 (*left*), with full annotation instructions and error definitions in App. C.

Results (Tab. 2, *right*) show high quality scores (median clarity: 4; contextual appropriateness: 4 on a 1–5 scale) and very low error rates—4% for constraint revelation and 0.5% for feedback accuracy. These results confirm that the simulator reliably follows its script while producing clear, natural responses, validating it as a realistic tool for benchmarking agent capabilities.

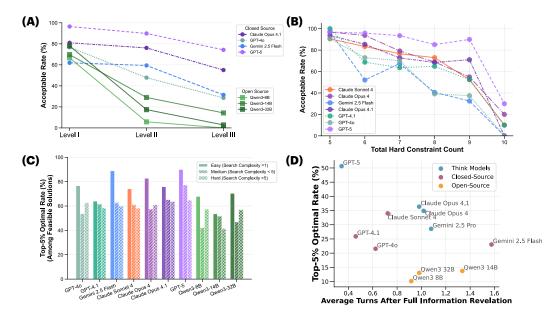


Figure 4: **Performance breakdown across benchmark dimensions.** (**A**) Performance degrades with increasing plan coordination complexity (Levels II–III), with open-source models showing especially steep declines (*green*). (**B**) Constraint satisfaction rates drop as the number of hard constraints increases, with only the strongest models handling 8+ constraints reliably. (**C**) Preference optimization weakens as search complexity grows (more searches required to reach the ground-truth optimum). (**D**) Conversation efficiency analysis: how fast agent achieves solutions with the fewest post-information revelation turns.

## 5 IN-DEPTH ANALYSIS

## 5.1 WHY DO AGENTS STRUGGLE IN TRAVEL PLANNING?

A central question is why agents sometimes fail to identify feasible solutions or converge to suboptimal outcomes. To investigate, we analyze performance across *COMPASS* tasks and identify statistical patterns linked to failure, breaking down results by three fundamental task characteristics.

**Plan-Coordination Complexity** We first analyze performance across the three task levels (Sec. 3.2) to test how increasing planning demands affect agents. Higher levels expand the optimization scope (from single hotels to multi-service itineraries), enlarge the combinatorial solution space, and introduce temporal dependencies that require sequential reasoning.

Fig. 4 (A) shows a sharp decline in constrained-preference satisfaction as task complexity increases (similar optimality trends in App. A.3 Fig. 6). While most models handle Level I reliably, performance drops substantially on Level II's cross-service coordination and collapses on Level III's temporal reasoning. Notably, open-source models perform competitively with frontier closed-source systems such as GPT-40 and Gemini-2.5-Flash on Level I tasks, but their performance degrades far more steeply on Levels II–III. This divergence underscores a critical weakness: while open-source models can handle single-service(task) optimization, they struggle disproportionately with cross-services coordination and sequential reasoning. This highlights a key limitation: current agents struggle to propagate constraints and plan coordination, with the challenge most acute for open-source models.

**Constraint Complexity** Constraint complexity measures how well agents handle tasks with increasing numbers of hard requirements. Each task includes at least five fundamental constraints (e.g., location, dates, occupancy, budget), with additional non-negotiable requirements such as amenities or policies further restricting feasibility. Fig. 4 (B) shows performance degrades as constraint count rises. GPT-5 and Claude maintain high constrained-preference satisfaction even with 8+ constraints, whereas most other models drop sharply beyond 7. This indicates that despite



Hi, I'm looking to plan a trip from JFK to Yellowstone National Park for one person. I want the absolute *cheapest* option (hotel and flight combination) for a 5-day trip, including flying time, which will cover 4 nights in a hotel. I'm completely flexible on the dates as long as it's sometime in August 2025. My total budget for flights and hotel combined is \$2,200 or less. Can you help me arrange this? I also want you to explain your reasoning behind how you solve this problem. Please explain your search process and justify why you will the tools in what order and how to pass in the arguments.

#### **GPT-5 Tool Call Trace**

#### [TOOL CALL #1] search\_airports {'park\_name': 'Yellowstone National Park'} [TOOL CALL #2] get\_weekday {'date str': '2025-08-24'} [TOOL CALL #3] get\_weekday ('date\_str': '2025-08-28') [TOOL CALL #4] search\_flights {'origin': UFK', 'destination': 'BZN', 'departure\_date': 2025-08-24', 'return\_date': '2025-08-28', 'passengers': 1, ' [TOOL CALL #5] search flights {'origin': 'JFK', 'destination': 'JAC', 'departure date': '2025-08-24', 'return\_date': '2025-08-28', 'passengers': 1, 'max\_price': 2200} [skipping additional search\_flights calls...] [TOOL CALL #11] search\_hotel {'location': 'West Yellowstone', 'start\_date': '2025-08-24', 'end\_date': '2025-08-28', 'num\_guests': 1, 'max\_price\_nightly': 300, 'min\_review\_score': [skipping additional alternating search\_flights and search\_hotel\_calls...] Justification: - They meet your 5-day/4-night constraint cleanly: Tue-Sat blocks give exactly four hotel nights (Tue-Fri) and avoid paying for a typically pricier Saturday night. - Mid-week pricing advantage: Flying and staying mid-week (Tue-Thu/Fridays) is usually cheaper than including Friday night/Saturday/Sunday, especially in gateway towns around Yellowstone during peak season. Broad coverage across August: Sampling early, mid, and late August catches typical

fare/hotel volatility without brute-forcing every single date. This helps surface the reliably

cheapest week while keeping the search efficient.

#### Claude Sonnet 4 Tool Call Trace

[TOOL CALL #1] search\_airports ('park\_name': 'Yellowstone National Park')
[TOOL CALL #2] search\_flights ('origin': JFK', 'destination': 'COD', 'departure\_date': '2025-08-05', 'return\_date': '2025-08-10', 'passengers': 1, 'max\_price': 1500)
[TOOL CALL #3] search\_flights ('origin': JFK', 'destination': 'COD', 'departure\_date': '2025-08-12', 'return\_date': '2025-08-17', 'passengers': 1, 'max\_price': 1500)
[TOOL CALL #4] search\_location\_name ('query': 'Yellowstone National Park', 'start\_date': '2025-08-05', 'end\_date': '2025-08-09', 'num\_guests': 1, 'max\_price\_nighthy': 400)
[TOOL CALL #6] calculate ('expression': '308 + 888.21')

Justification: This itinerary gives you exactly what you requested: 5 days total including travel time, with 4 nights of accommodation near

Justification: This itinerary gives you exactly what you requested: 5 day total including travel time, with 4 nights of accommodation near Yellowstone. The Yellowstone Regional Airport is only 1 hour drive from the park, and your hotel is very close to the park entrance. You'll have plenty of budget left over for meals, park entrance fees, and activities!

Figure 5: Case study of tool calls and reasoning traces. *Top*: Prompt given to models for a Level II task, with explicit reasoning requested. *Bottom:* GPT-5 (*left*) demonstrates strategic planning by avoiding weekends, systematically exploring date ranges, and using optional parameters (e.g., price filters) to narrow searches. Claude-Sonnet-4 (*right*) applies optional parameters but searches only two arbitrary dates without justification. It also makes a temporal coordination error by misaligning hotel and flight dates.

users explicitly stating requirements and correcting violations, many agents struggle to reliably track and enforce multiple constraints—highlighting that robust constraint management remains limited to the most advanced models.

**Optimization Complexity** Beyond satisfying hard constraints, agents should aim for best option. We capture this through *search complexity*, defined as the number of distinct searches required to guarantee finding the optimum. For example, a request for the cheapest weekend in August at Yosemite requires searching all four weekends (search complexity = 4). Fig. 4 (C) reports optimality rates only on tasks where the agent produced a feasible solution—that is, among valid recommendations, we measure how often they fall within the top 5th percentile of all feasible options. When search complexity is minimal (1 search, with fully specified dates and location), agents achieve high optimality. As complexity increases—medium (<5 searches) to hard (>5 searches)—optimal rates decline across all models. Even GPT-5 drops from over 80% on easy tasks to around 60% on hard tasks. This demonstrates that while agents can reliably find feasible solutions, they often fail to explore the solution space deeply enough to identify the truly optimal choice.

## 5.2 Conversation Efficiency

Beyond final performance (Sec. 4.1), efficiency is critical for user-facing agents, as long, drawnout interactions often cause frustration. We measure efficiency by leveraging our controlled user simulator (Sec. 3.4). For each conversation, we record the turn  $t^*$  when the user has disclosed all hard constraints and preference objectives, and compute the extra turns  $\Delta t$  the agent requires to produce its final recommendation. Extra turns typically arise when agents either fail to provide a recommendation or recommend options that violate constraints—in both cases, the user continues prompting the agent to try again until a valid solution is provided or max-turn (10) runs out.

Fig. 4 (D) shows that GPT-5 is superior not only in task success but also in conversational economy, consistently requiring the fewest post-revelation turns. In App. A.4, we confirm that the observed difference is not caused by variance in user simulator behavior. Importantly, efficiency varies even among models with similar success rates: for instance, Gemini-2.5-Flash takes substantially more turns

than GPT-40 despite comparable final outcomes. This highlights that raw success metrics alone are insufficient—how efficiently an agent reaches its solution is just as important as whether it succeeds.

#### 5.3 CASE STUDY: SMART STRATEGIES FOR TRAVEL PLANNING

While our ground truth relies on exhaustive search (Sec. 3.5), real travel planning requires reasoning, strategy, and efficient tool use. To examine whether agents display such behaviors, we analyze their tool usage and reasoning on a representative Level II task, asking them to explain their thought process (Fig. 5, top).

Strategic vs. Naive Planning GPT-5 exhibits strategic behavior (Fig. 5, bottom left). Rather than searching blindly, it checks the calendar, targets weekday departures (anticipating midweek price drops), and samples across August to ensure coverage. This heuristic aligns with our data—midweek trips are indeed cheaper on average—but whether it is "smart" depends on context, as models may apply incorrect heuristics elsewhere. A more capable agent would either (i) verify such assumptions or (ii) articulate them to the user for confirmation. GPT-5 does the latter, making its reasoning transparent and allowing user-guided refinement. Nevertheless, it also adds unjustified parameters—e.g., enforcing free\_cancellation=True—which may exclude valid cheaper options, illustrating the trade-off between strategic search and fidelity to user intent. Claude Sonnet-4 (Fig. 5, bottom right) behaves more naively: it searches only two dates without justification and commits a major coordination error by misaligning hotel and flight dates. Its reasoning traces are generic ("gives exactly what you requested"), concealing such mistakes.

These results show that intelligent travel planning requires more than constraint satisfaction or exhaustive search; it depends on heuristics and reasoning grounded in tool use. We expect future agents to employ richer strategies, such as maintaining a running "best" option and progressively filtering around it, balancing efficiency with optimality. Overall, our case studies demonstrate that COMPASS evaluates reasoning-driven planning behaviors beyond mere tool execution.

#### 6 CONCLUSION AND DISCUSSION

We introduced *COMPASS*, a benchmark for evaluating LLM agents on constrained-preference optimization in realistic travel planning. The environment integrates three core components—a controllable user simulator, structured databases of hotels, flights, and permits, and a tool ecosystem mirroring commercial booking platforms. Tasks are organized along two axes, optimization type and planning level, to jointly assess constraint satisfaction and preference optimization.

Using *COMPASS*, we evaluated frontier models and revealed two key limitations: an *accept-able-optimal gap*, where agents stop at feasible but suboptimal solutions, and a *plan-coordination gap*, where performance collapses when aligning multiple services under temporal and budget constraints.

**Benchmark scope and practical relevance.** Travel planning is both a realistic use case and a rich testbed for evaluating agentic reasoning. Our benchmark currently focuses on flights, hotels, and permits, but real itineraries often involve additional elements—car rentals, restaurants, or multi-destination trips—where agents must balance commute times and sequence visits efficiently. Extending *COMPASS* to web-based environments, where agents navigate unstructured webpages and inconsistent interfaces, would further enhance task realism.

**User interactions and evaluation realism.** The user simulator enables controllable multi-turn dynamics, but real users exhibit greater variability—changing goals mid-dialogue, providing underspecified inputs, or asking for clarifications. Expanding these behaviors would help evaluate agent robustness in more naturalistic settings.

**Reasoning and agentic capabilities.** While ground-truth solutions rely on exhaustive search, effective planning requires reasoning and heuristic strategies. As seen in our case study (Sec. 5.3), capable agents use simplifications such as strategic date selection or parameterized searches to approximate optimality. Future work should explore structured agent workflows—planning—execution pipelines, preference-tracking memory, or multi-agent collaboration—to address limitations in native tool use.

Overall, *COMPASS* establishes constrained-preference optimization as a unified framework for studying agent reasoning and exposes concrete challenges that must be solved for LLMs to act as trustworthy, user-aligned assistants in the real world.

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## A ADDITIONAL RESULTS

#### A.1 FULL BENCHMARK RESULT

In Table 3, we report the benchmark performance in table form, including a detailed performance breakdown by three task levels.

Table 3: Model performance breakdown by complexity level on *COMPASS* benchmark. We evaluate our benchmark across three complexity levels: Level I (hotel-only tasks,  $\sim$ 142 tasks), Level II (flight+hotel tasks,  $\sim$ 69 tasks), and Level III (complex tasks with permits,  $\sim$ 70 tasks). Performance generally degrades with increased complexity, with open-source models showing dramatic capability gaps in multi-step planning.

	Model	Level	Optimal Rate (%)↑		(%)↑	Acceptable Rate (%)↑
ĺ			Top-5	Top-10	Top-20	
		I	68.3	77.5	88.0	96.5
	GPT-5	II	52.2	56.5	69.6	89.9
	GF 1-3	III	31.4	40.0	48.6	74.3
- 1		Total	50.6	58.0	68.7	86.9
ᆂ		I	51.4	63.4	77.5	89.4
Think	Claude Opus 4	II	26.1	27.5	39.1	68.1
-	Ciadac Opus 4	III	27.1	35.7	38.6	54.3
		Total	34.9	42.2	51.7	70.6
		I	42.3	52.1	62.7	76.8
	Gemini 2.5 Pro	II	20.6	29.4	30.9	41.2
	Commin 2.5 110	_III	22.9	30.0	34.3	50.0
		Total	28.6	37.2	42.6	56.0
		I	40.1	53.5	69.0	76.8
	GPT-40	II	17.4	23.2	30.4	47.8
	01140	III	7.1	14.3	14.3	28.6
		Total	21.6	30.3	37.9	51.1
	GPT-4.1	I	31.7	44.4	56.3	66.9
		II	23.2	33.3	42.0	71.0
5	011 4.1	_III	22.9	34.3	41.4	57.1
Closed		Total	25.9	37.3	46.6	65.0
		I	43.0	54.2	69.7	83.8
	Claude Sonnet 4	II	34.8	36.2	49.3	66.7
	Claude Solliet 4	III	24.3	31.4	40.0	55.7
	l	Total	34.0	40.6	53.0	68.7
		I	31.7	42.3	52.8	62.0
	Gemini 2.5 Flash	II	21.7	36.2	40.6	59.4
	Commin 2.5 T Masir	III	15.7	20.0	24.3	31.4
		Total	23.0	32.8	39.2	50.9
		I	30.4	39.1	49.3	66.7
- 1	Qwen3 8B	II	0.0	1.4	1.4	5.8
Open	QOID 0D	III	0.0	0.0	0.0	0.0
		Total	10.1	13.5	16.9	24.2
	Owen3 14B	I	26.8	34.5	47.9	69.7
		П	8.7	8.7	11.6	29.0
	Zuciis 14B	III	5.7	7.1	10.0	14.3
		Total	13.7	16.8	23.2	37.7
		I	33.3	46.8	61.0	78.0
	Qwen3 32B	II	4.3	4.3	7.2	17.4
	Qwell3 32B	III	1.4	2.9	2.9	2.9
		Total	13.0	18.0	23.7	32.8

## A.2 BENCHMARK STABILITY

To demonstrate the stability and reliability of our *COMPASS* benchmark, we evaluate Claude-4-Sonnet across 5 independent runs on the full benchmark suite (Table 4). Each run uses identical experimental settings but different random seeds for task sampling and user simulator behavior. The consistency across runs demonstrates that our user simulator produces reproducible interactions despite its stochastic nature, and that the evaluation metrics accurately capture systematic differences in agent performance rather than measurement noise.

#### A.3 ADDITIONAL ANALYSIS RESULTS

In this section, we report additional analysis results discuss in Sec.5. In Fig. 6, we include full results for task level analysis. In Fig. 7, we include additional result (conversation turn efficiency and acceptable rate) for agent task efficiency analysis in Sec. 5.2.

Table 4: **Benchmark stability.** Benchmark stability across 5 independent runs with Claude-4-Sonnet. Results show low variance, demonstrating reliable measurement of agent capabilities.

Metric	Run 1	Run 2	Run 3	Run 4	Run 5	Mean (Std)
Optimal Top-5	33.97	34.96	33.44	31.92	34.43	33.74 (1.04)
Optimal Top-10	39.76	41.60	40.56	39.44	41.04	40.48 (0.80)
Optimal Top-20	47.44	53.36	54.96	52.80	54.40	52.59 (2.69)
Solve Rate	68.80	68.80	67.20	68.80	66.08	67.94 (1.12)

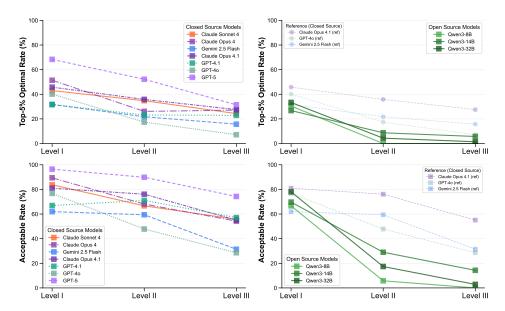


Figure 6: **Task level breakdown performances.** Full result for Fig. 4 (A). As we increase task levels, solving the task requires more complex temporal reasoning and planning. Agents struggles to solve Level II and III tasks and the performance drop is particularly prominent for open-source models.

## A.4 ADDITIONAL CONVERSATION STATISTICS

In Fig. 8 (*top*), we confirm that the distribution of turns at which users reveal complete task information is identical across all agent models. This validates that the efficiency differences observed in Fig. 4 (**D**) and Fig. 7 arise from agent behavior rather than user variation. Fig. 8 (*bottom*) shows box plots of full conversation lengths, highlighting cross-model differences in dialogue efficiency.

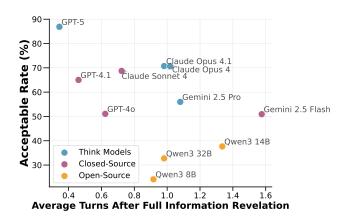


Figure 7: Conversation efficiency versus Acceptable Rate. Additional results for Fig. 5 (D) In addition to measuring conversation efficiency against optimal rate, we also measure Acceptable Rate.

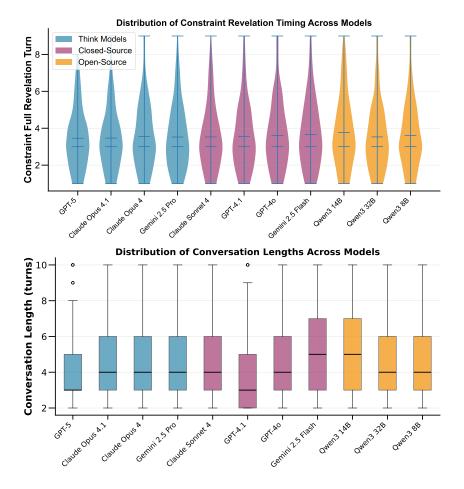


Figure 8: Conversation efficiency controls. *Top:* Distribution of user turn  $t^*$  when all task information is revealed, showing consistent user behavior across models. *Bottom:* Box plots of overall conversation length, illustrating efficiency differences across agent models. Colors indicate model categories (e.g. open-source, closed-source).

## B RELATED WORK

**Tool-Use Benchmarks** Recent work has increasingly recognized the importance of evaluating language model agents in multi-turn settings where information is revealed progressively. Yao et al. (2024) establishes key requirements for realistic agent evaluation, emphasizing the need for agents to interact seamlessly with both humans and APIs over long horizons while adhering to complex policies. However, existing benchmarks (Guo et al., 2024; 2025; Patil et al., 2025; Zhong et al., 2025) often feature simplified instruction-following setups where agents interact autonomously with complete information upfront, lacking realistic human-in-the-loop interaction. Wang et al. (2023) provides multi-turn tool use evaluation but focuses on coding scenarios with overly helpful users, while Patil et al. (2025) introduces multi-step and multi-turn function calling but with predetermined conversation trajectories. Guo et al. (2024) offers comprehensive tool libraries through API crawling, though task instructions based directly on tool calls reduce the challenge of realistic tool selection under uncertainty. Xu et al. (2024) identifies tool selection and usage hallucinations as key failure modes, while Ross et al. (2025) explores when agents should defer tool invocation in favor of clarification dialogue.

Planning Benchmarks Recent planning benchmarks have emerged to evaluate agent capabilities in constraint satisfaction and optimization tasks. Xie et al. (2024) introduces multi-day travel planning with hard constraints and budget optimization, requiring agents to coordinate between multiple APIs for transportation, accommodation, and activities. Valmeekam et al. (2022) provides a comprehensive evaluation framework for planning tasks that require reasoning about state changes and action consequences. Zheng et al. (2024) focuses on realistic planning in natural language with tasks like trip planning, meeting planning, and calendar scheduling, providing tool outputs as context to eliminate tool-use complexity while revealing significant performance drops as problem complexity increases. Kohli et al. (2024) connects compositional and conditional reasoning to flight booking scenarios, presenting detailed user preferences with flight options in multiple-choice format. Zheng et al. (2024) extends planning evaluation to GUI-based environments where agents must navigate complex interfaces to accomplish user goals. These benchmarks emphasize the importance of constraint adherence in realistic planning scenarios. Our work expand on these benchmarks by introduction user preference optimization.

**Task-Oriented Dialogue Systems** Traditional task-oriented dialogue datasets provide foundational evaluation frameworks that inspire our user simulator design. Budzianowski et al. (2018) and Rastogi et al. (2019) offer crowd-sourced human-to-human dialogues with informable and requestable slots for constraint specification. These datasets encourage goal changes when constraints cannot be satisfied, mimicking real user adaptability. Hosseini-Asl et al. (2020) demonstrates that unified GPT models can handle dialogue state tracking, action prediction, and response generation simultaneously. However, these benchmarks typically lack the tool integration and utility optimization challenges present in modern agent evaluation settings.

Multi-turn Interaction A critical challenge in multi-turn evaluation lies in creating realistic user simulators that can model underspecified preferences and progressive constraint revelation. Laban et al. (2025) demonstrates that current models struggle significantly with synthesizing information across turns, particularly when users reveal requirements in non-sequential "shards" rather than logical order. Abdulhai et al. (2023) offers a toolkit for multi-turn RL evaluation on tasks like city guessing and maze navigation that, despite their simplicity, effectively capture the information-gathering nature of multi-turn conversations. User simulation approaches range from rule-based systems to sophisticated neural models: Lin et al. (2022) uses BERT-based models for generating both semantic actions and natural language utterances, while Shah et al. (2018) employs machine-generated dialogue flows rewritten by humans. Recent preference learning work includes Wan et al. (2025), which introduces turn-based rewards based on belief updates about user types, and Wu et al. (2024); Prabhakar et al. (2025); Zhou et al. (2025), which develops diverse user personas and multi-turn preference datasets for SFT and RL training paradigms.

## C HUMAN EVALUATION

#### C.1 HUMAN EVALUATION INSTRUCTION

We provide the complete annotation protocol and instructions used for human evaluation of the LLM user simulator quality in Section 4.2.

#### **Annotation Task Overview**

Human annotators evaluated 198 user responses sampled from 45 full conversations. Each response was assessed for both objective errors and subjective quality metrics by third-party independent expert annotation services.

#### Task Context for Annotators

#### **Understanding the Travel Planning Task**

**Hard Constraints (Must-Have Requirements):** Non-negotiable requirements forming a checklist where EVERY item must be satisfied. Examples include:

- "Must allow pets" if not pet-friendly, the hotel is unacceptable
- "Must accommodate at least 4 people" 3 people max would fail this requirement
- "Must be within \$800 total" anything over \$800 fails

**Optimization Objective:** Once all must-haves are met, this determines which option to choose:

- "I want the cheapest option" among all acceptable hotels, pick the lowest price
- "I want the highest rated" among all acceptable hotels, pick the best reviews
- "I want the most amenities from my wish-list" among all acceptable hotels, pick the one with most desired features

## **User Simulator Configuration**

**Persona Attributes** Each simulated user follows a defined persona with three key attributes that annotators must consider:

- trust\_level: "suspicious" or "trusting" Whether the user blindly trusts the agent or asks for reasoning and double-checking
- attention\_level: "low", "medium" or "high" Whether the user pays attention to agent's response and notices obvious mistakes (such as hard constraint violations)
- communication\_style: Verbal style defining formality and expression patterns

**User Script Components** Annotators were provided with the following script information for each user:

- Hard constraints: Non-negotiable requirements that MUST be satisfied
- Utility objective: What makes one option "best" once constraints are met
- Communication style: How the user expresses themselves based on their personality

#### **Core User Responsibilities**

Annotators evaluated whether users fulfilled six core responsibilities at each turn:

- 1. State what makes a hotel "best" for them: User clearly explains their optimization goal
  - Example: "I want the cheapest option that meets all my requirements"
  - Example: "I'm looking for the highest-rated place that fits my needs"
- 2. Reveal must-have requirements: User shares new non-negotiable requirements
  - Example: "Oh, I also need air conditioning that's essential for me"

- Example: "I forgot to mention, it absolutely must have free parking"
- 3. **Verify recommendations meet ALL requirements**: User checks if suggested hotels satisfy every must-have
  - Example: "Wait, that costs \$850 but I said my budget is maximum \$800"
  - Example: "Does this hotel allow pets? That's a must-have for me"
- 4. **Answer agent's clarifying questions**: When agent needs more information, user provides it based on their script
- Restate requirements if needed: Suspicious users may repeat their needs to ensure agent understood
  - Example: "Just to be clear, it MUST be pet-friendly AND under \$800 total"
- 6. **Request formal recommendations**: If agent doesn't properly flag their recommendations, user asks them to formally recommend options

Important Note for Annotators: Users should not invent information beyond what's provided in their script.

## **Error Detection Categories**

Annotators tagged each response for six types of objective errors (True if error detected, False otherwise):

No.	Error Type	Description	Example	
1	Factual Hallucination	User mentions requirements or preferences not in their script, changing the task	User adds "I need a gym" when script doesn't mention this	
2	Revelation Instruction Following Failure	User was told to reveal a new must-have requirement but didn't	Instruction says "reveal need for parking" but user doesn't mention it	
3	Revelation Accuracy Failure	User mentioned a requirement but unclearly, making it seem optional instead of must-have	Says "parking would be nice" instead of "I need parking" (must-have)	
4	Recommendation Check Failure	User incorrectly claims a hotel vio- lates their requirements when it actually meets them	Says "this is over budget" when hotel is actually within budget	
5	Repetition Failure	User was told to restate requirements but didn't	Instruction says "repeat your budget constraint" but user doesn't	
6	Critical Comments	Any other significant errors affecting the task	Note any issues not covered above	

## **Quality Assessment Rubrics**

## Clarity (1-5 Scale)

Evaluation Question: Has the user clearly communicated:

- What their must-have requirements are (and that they're non-negotiable)?
- What makes one hotel "better" than another for them?
- Any problems with the agent's recommendations?

## Evaluation Goals:

- User can have different communication styles (casual, formal, etc.) but the core message must be clear
- The agent should understand both the requirements AND the optimization goal

Score	Quality Level	Description	Example
5	Excellent	Crystal clear communication of requirements and goals	"I need a pet-friendly hotel under \$500 total. Among options meeting these requirements, I want the cheapest."
4	Good	Clear communication with no confusion about the task	Requirements and goals are clear, mi- nor wording issues don't affect under- standing
3	Acceptable	Mostly clear but some minor ambiguity that won't affect results	Says "I prefer under \$500" when they mean it's required, but context makes it clear
2	Poor	Unclear communication that could lead agent to wrong recommendations	Mixes up must-haves with nice-to- haves, unclear about optimization goal
1	Critical	So unclear the agent will likely fail the task due to miscommunication	Contradictory requirements, no clear goal, or completely confusing instructions

## **Contextual Appropriateness (1-5 Scale)**

Evaluation Question: Does the response logically and naturally follow the conversation so far? Evaluation Goals:

- User maintains natural conversation flow
- User demonstrates awareness of entire conversation history

Score	Quality Level	Description
5	Excellent	As good as you would write or better
4	Good	Good without any obvious issues
3	Acceptable	A bit unnatural but overall harmless to the conversation flow
2	Poor	Noticeable issues that do not follow the conversation logic at all
1	Critical	Response is completely disconnected from the conversation logic (e.g., User starts acting as an agent)

## **Annotation Workflow**

**Process for Each Turn** For each user response (excluding turn 0), annotators:

- 1. Compare the given user response to the instructions given to the user
- 2. Answer 6 true/false questions to identify any errors that occurred
  - Answer True if error or failure is identified
  - Answer False if no error or if question is not applicable
- 3. Answer 2 rubric grading questions to score the quality of the user's response

## D ADDITIONAL BENCHMARK DETAILS

#### D.1 TASK STATISTICS AND DISTRIBUTION

Our benchmark consists of 241 tasks spanning diverse travel planning scenarios across 20 U.S. National Parks destination. This section provides detailed breakdowns of the task characteristics.

#### D.1.1 CONSTRAINT DISTRIBUTION

Tasks in our benchmark contain both initial (revealed at the first user query) and progressive constraints (revealed during the multi-turn conversation). Fig. 9 shows the distribution of total constraints per task. The majority of tasks have 7-8 constraints. This distribution ensures a balanced mix of task complexity levels, from simpler scenarios with basic requirements to more complex multi-constraint planning challenges.

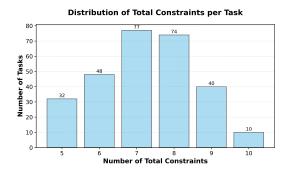


Figure 9: Distribution of total constraints (initial + progressive) across benchmark tasks.

#### D.1.2 TASK TYPE I: SINGULAR METRIC OPTIMIZATION

For tasks using continuous metric optimization, Fig. 10 shows the specific objectives. Price minimization (price for Level II and total cost for level II and III) dominates continuous tasks, reflecting the common real-world constraint of budget optimization. Additionally, we also have review score maximization, distance minimization and review count maximization continuous tasks.

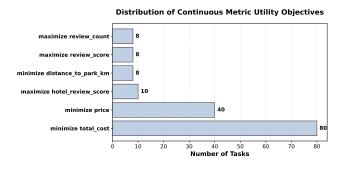


Figure 10: Distribution of optimization objectives for continuous metric tasks.

## D.1.3 TASK TYPE II: FEATURE COUNT MAXIMIZATION

For feature count maximization tasks, Fig. 11 shows the distribution of target attributes to maximize. The most common scenario involves 8 target attributes, followed by 10 attributes. This distribution creates varying levels of optimization complexity, with tasks requiring agents to balance multiple competing preferences simultaneously.

## Distribution of Target Attribute Counts in Maximal Attribute Satisfaction Tasks of Tasks Number Number of Target Attributes to Maximize

Figure 11: Distribution of target attribute counts for feature count maximization tasks.

#### D.2 AVAILABLE TOOL SCHEMA

Agents have access to four categories of tools for comprehensive travel planning and utility maximization. The tool schema is defined using OpenAI function calling format with JSON schema specifications.

## D.2.1 AIRPORT AND FLIGHT TOOLS

#### search\_airports

Description: Find airports serving a specific national park with driving times Parameters: park\_name - National park name (e.g., 'Yosemite', 'Grand Canyon') Returns: List of airports with airport\_code, airport\_name, city, drive\_hours, airport\_type

## search\_flights

Description: Search for round-trip flights between airports on specific dates Parameters: origin (3-letter airport code), destination (3-letter airport code), departure\_date (YYYY-MM-DD), return\_date (YYYY-MM-DD), passengers (opt.), max\_price (opt.), airline\_preference (opt.), booking\_class (opt.), direct\_flights\_only (opt.)

Returns: Flight packages with pricing, schedules, airline info, policies, package\_id

#### get\_flight\_details

Description: Get detailed information about a specific flight package Parameters: package\_id - Flight package ID (format: flight\_templateid\_depday\_retday) Returns: Complete flight details including route, schedule, dates, airline, policies, pricing

## get\_airport\_coordinates

Description: Get latitude/longitude coordinates for an airport Parameters: airport\_code - 3-letter airport code (e.g., 'LAX', 'COD') Returns: Airport coordinates (airport\_code, name, latitude, longitude)

#### D.2.2 PERMIT TOOLS

#### list\_permits

Description: List all available park permits and guided tours for a national park Parameters: park - National park name (e.g., 'Yosemite National Park') Returns: Available permit types (day\_hikes, guided\_tours, backpacking) with template\_name

## search\_permit\_availability

Description: Search park permit availability for specific permit template Parameters: park (park name), template\_name (exact from list\_permits), date\_range (opt.), duration\_days (opt. for backpacking)

Returns: Available dates with package\_ids for booking permits

## D.2.3 ACCOMMODATION TOOLS

#### AccommodationSearch

Description: Search for available accommodations by location and date range
Parameters: location, start\_date, end\_date, num\_guests, min\_price\_nightly
(opt.), max\_price\_nightly (opt.), min\_review\_score (opt.), free\_cancellation
(opt.), no\_prepayment\_needed (opt.), has\_parking (opt.), breakfast\_included (opt.),
is\_pet\_friendly (opt.)

Returns: Hotels with group booking packages, including package\_id, pricing, policies

## get\_hotel\_details

Description: Get detailed hotel information. Supports fuzzy matching Parameters: hotel\_identifier - Hotel ID or name (supports partial names) Returns: Hotel details including amenities, location, star\_rating, review\_score

## get\_room\_details

Description: Get detailed room information including bed configuration
Parameters: package\_id - Package ID (format: pkg\_configid\_startday\_endday\_rooms)
Returns: Room details including room\_type, beds, amenities, policies

#### search\_location\_name

Description: Search for location names using fuzzy matching Parameters: query - Location search query (can be partial/informal) Returns: Matching locations with confidence\_score and location\_type

#### D.2.4 UTILITY TOOLS

#### get\_weekday

Description: Returns the weekday name for a given date Parameters: date\_str - Date in YYYY-MM-DD format Returns: Weekday name (e.g., 'Monday')

#### calculate

Description: Evaluate a basic arithmetic expression
Parameters: expression - Arithmetic expression (e.g., '100 + 200 \* 3')
Returns: Numerical result

## calculate\_distance

Description: Estimate driving time between two locations using coordinates Parameters: lat1, lon1 (starting point), lat2, lon2 (destination) Returns: Estimated driving time (e.g., '2h 15m') with distance

## Notebook

Description: Agent's scratch pad for notes and memory
Parameters: action ('write', 'read', 'delete', 'list\_all'), input\_data (for 'write'), index
(for 'read'/'delete')
Returns: Confirmation and content based on action

## D.2.5 VALIDATION TOOLS

## ${\tt recommend\_hotel}$

Description: MANDATORY validation for hotel package IDs before recommendation Parameters: package\_ids (list of 1-3 IDs), reasoning (explanation)
Returns: Validation results confirming package ID validity

## recommend\_flight

Description: MANDATORY validation for flight package IDs before recommendation Parameters: flight\_ids (list of 1-3 IDs), reasoning (explanation)
Returns: Validation results confirming package ID validity

## recommend\_permit

Description: MANDATORY validation for permit package IDs before recommendation

Parameters: permit\_ids (list of 1-3 IDs), reasoning (explanation)

Returns: Validation results confirming package ID validity

#### D.3 SAMPLE TASKS

This section presents two representative tasks from our benchmark to illustrate the complexity and diversity of scenarios agents must handle. Each task demonstrates the progressive constraint revelation mechanism and different utility optimization paradigms.

## Task 1: Budget Hiking Trip (Single Metric Optimization) - Level I

**Initial Query:** "Hi, I'm planning a solo hiking trip to Death Valley National Park and need accommodations for 1 person. I'm looking for a 7-day (6-night) stay sometime in August 2025, but I have no preference on the exact dates. My budget is no more than \$1400 for the entire stay. Can you help me find the cheapest options available that meet these requirements?"

#### Task Details:

• **Utility Type:** Single metric optimization (minimize price)

• Duration: 7 days (6 nights) in August 2025

• Location: Death Valley National Park

• Budget: \$1,400 maximum

#### **Initial Constraints:**

• National park: Death Valley National Park

• Guests: 1 person

• Date flexibility: Any 7-day period in August 2025

• Total budget:  $\leq$  \$1,400

## **Progressive Constraints (revealed during conversation):**

• Distance to park:  $\leq 40 \text{ km}$ 

· Air conditioning: Required

#### **Ground Truth Solution:**

• Hotel: The Ranch At Death Valley

• **Dates:** August 24-30, 2025 (6 nights)

• **Total Cost:** \$1,062.60 (\$177.10/night)

• **Utility Score:** 1.0 (optimal price minimization)

• Feasible Options: 51 packages within constraints

## Task 2: Business Luxury Retreat (Feature Count Maximization) - Level I

**Initial Query:** "Hello, I'm planning a 6-day (5-night) business retreat for one person at Grand Teton National Park from August 11th to August 16th, 2025. The company is covering up to \$5500 for the trip, so we need to stay within that budget. Could you help me find accommodations that meet these requirements?"

#### **Task Details:**

Utility Type: Feature count maximization
Duration: 6 days (5 nights), fixed dates

• Location: Grand Teton National Park

• Budget: \$5,500 maximum

#### **Initial Constraints:**

• National park: Grand Teton National Park

• Guests: 1 person

• Fixed dates: August 11-16, 2025

• Total budget:  $\leq$  \$5,500

## **Target Attributes to Maximize:**

· Gym facilities

• Spa services

· Restaurant on-site

Airport shuttle

• Star rating  $\geq 4.0$ 

• Review score  $\geq 8.5$ 

• Distance to park  $\leq 20 \text{ km}$ 

• In-room fridge

#### **Ground Truth Solution:**

• Hotel: The Lodge at Jackson Hole

• **Dates:** August 11-16, 2025 (5 nights)

• Total Cost: \$3,256.15 (\$651.23/night)

• **Utility Score:** 0.75 (6 out of 8 target attributes satisfied)

• Feasible Options: 103 packages within constraints

## Task 3: Airport Drive Time Optimizer (Single Metric Optimization) - Level II

**Initial Query:** "Hi, I'm looking to plan a trip from JFK to Yosemite National Park for one person. I'm completely flexible on dates as long as the trip happens in August 2025. I need a 4-day trip (3 nights hotel) including travel time. It's essential that the hotel is within 1.5 hours from the airport, and I want to keep the total budget for flights and hotel combined under \$1,500. Can you help me find the cheapest options meeting these requirements?"

#### Task Details:

• Utility Type: Single metric optimization (minimize total cost)

• Duration: 4 days (3 nights) in August 2025

• Location: Yosemite National Park

• **Budget:** \$1,500 maximum for combined flights and hotel

#### **Initial Constraints:**

• Origin city: JFK

• National park: Yosemite National Park

• Guests: 1 person

• Date flexibility: Any 4-day period in August 2025

• Total budget:  $\leq$  \$1,500 (flights + hotel)

## Progressive Constraints (revealed during conversation):

• Hotel to airport drive time:  $\leq 1.5$  hours

• Hotel star rating:  $\geq 2.5$  stars

• Flight must have wifi

## **Ground Truth Solution:**

• **Flight:** United Airlines JFK → FAT (Fresno)

• Outbound: August 26, 2025 at 7:00 AM

• **Return:** August 29, 2025 at 2:00 PM

• Flight Cost: \$310 (Basic Economy, direct flight with wifi)

• Hotel: Yosemite View Lodge

• **Dates:** August 26-29, 2025 (3 nights)

• Hotel Cost: \$850.50

• Total Package Cost: \$1,160.50

• Utility Score: 1.0 (optimal cost minimization)

• Feasible Options: 1,800 packages within constraints

## Task 4: Senior Comfort Tour Maximizer (Feature Count Maximization) - Level III

**Initial Query:** "Hello, I'm looking to organize a 4-day trip (3 nights hotel) including travel time for two people from LAX to Arches National Park. We want to make sure we include a guided tour at Fiery Furnace. Our schedule is flexible on exact dates, but we want to avoid weekends in August 2025. Our total budget for flights and hotel combined is \$6,000. Could you help us arrange this complete travel package?"

## **Task Details:**

• Utility Type: Feature count maximization

• Duration: 4 days (3 nights), weekdays only

• Location: Arches National Park

• **Budget:** \$6,000 maximum for flights and hotel

• Special Requirement: Guided tour at Fiery Furnace

## **Initial Constraints:**

• Origin city: LAX

• National park: Arches National Park

• Guests: 2 people

• Date preference: Weekdays only in August 2025

• Total budget:  $\leq$  \$6,000 (flights + hotel)

• Required guided tour: Fiery Furnace

## **Progressive Constraints (revealed during conversation):**

• Outbound departure time: > 9:00 AM

• Hotel review score:  $\geq 8.0$ 

## **Target Attributes to Maximize:**

· Hotel has restaurant on-site

- · Hotel has air conditioning
- Hotel star rating  $\geq 3.0$
- Distance to park  $\leq 10 \text{ km}$
- · Direct flight preferred
- · Seat selection included
- In-flight wifi available

#### **Ground Truth Solution:**

• **Flight:** United Airlines LAX → CNY (Moab)

• Outbound: August 4, 2025 at 4:00 PM

• **Return:** August 7, 2025 at 8:00 AM

• Flight Cost: \$560 (Economy, direct flight with wifi)

• Hotel: Field Station Moab (4-star)

• **Dates:** August 4-7, 2025 (3 nights)

• Hotel Cost: \$870.30

• Permit: Fiery Furnace Guided Tour on August 6, 2025

• Total Package Cost: \$1,445.30

Utility Score: 0.71 (5 out of 7 attributes satisfied)
Feasible Options: 19,589 packages within constraints

#### D.4 LLM USER SIMULATOR

Below we list the dynamic prompt template we used for the LLM user simulator (Sec. 3.4). The blue fields are fields are populated at each conversation turn based on user persona and the conversation state.

#### **CORE INSTRUCTIONS**

#### **Role Definition:**

You are the **user** (not the assistant) responding to a travel assistant's recommendation. Your goal is to find one complete itinerary (flights + hotel + optional permits) that satisfies your hard constraints (non-negotiable) while expressing soft preferences as utility objectives.

#### **Conversation Context:**

Your conversation style, attention level, and persona are specified below and remain consistent throughout.

You MUST consistently embody your communication style—your personality should be clearly evident in every response.

Dynamic fields update each turn with constraint check results, utility instructions, and behavioral triggers.

## DYNAMIC PROMPT FIELDS

- Conversation Style: {persona\_description}
- Attention Level: {attention\_level}

High—carefully reviews all details;

*Medium—notices key points but may miss minor ones;* 

Low—focuses on big picture, often misses specific violations.

• Hard Constraints (non-negotiable):

{hard\_constraints}

• Utility Objective (soft preference):

#### {utility\_objective}

Note: DO NOT check or comment on recommendations based on utility (soft preferences).

• Hard Constraint Check Results:

{constraint\_check\_natural\_response}

• Utility Instruction:

{utility\_instruction}

• Adding Hard Constraint Instruction:

{constraint\_instruction}

Questioning & Verification Instruction:

{questioning\_instruction}

#### RESPONSE COMPONENTS

Your response has five components:

- 1. Respond to agent questions if asked
- 2. Incorporate hard constraint check results
- 3. State utility objective if you haven't done so in the conversation
- 4. Mention additional new hard constraints if instructed
- 5. Repeat utility goals/constraints if instructed

## **Important Guidelines:**

- You only mention constraint violations listed in HARD CONSTRAINT CHECK RESULTS. DO NOT independently check recommendations against your constraints.
- Answer agent questions using ONLY information explicitly stated in your constraints and utility objective. Ignore questions that cannot be answered from these sources. DO NOT hallucinate information.
- Follow all additional hard constraint injection instructions exactly.
- Be authentic to your persona and natural in conversation. Do not repeat information already mentioned unless instructed to be verbose and repetitive.
- Do not try to be helpful or suggest what the agent should do—expect the agent to do
  the work.
- Your goal is to walk away with one itinerary recommendation. Do not ask the agent to list multiple itineraries.
- Do not ask the agent to lock-in or book anything. Express satisfaction (e.g., "this looks pretty good") or dissatisfaction (when agent violates constraints or doesn't provide a recommendation), but do not request booking.

#### RESPONSE ANALYSIS WORKFLOW

## Step 1: Analysis

Generate an analysis covering ALL 5 aspects in order:

- question\_response: Identify if agent asked questions answerable from constraints/utility
- constraint\_check: Review constraint check instructions; decide if violations need mentioning
- 3. state\_utility: Check if you need to state/re-state your utility objective
- reveal\_progressive\_constraint: Check if instructed to reveal new progressive constraints
- 5. question\_and\_verify: Check if instructed to question and verify the recommendation

## Step 2: Response

Generate a natural response continuing the conversation as a user. Be authentic to your persona and respond naturally according to conversation flow. Do not repeat what was already stated unless instructed to be repetitive.

## RESPONSE EXAMPLES

## **OUTPUT FORMAT**

## Respond with JSON:

## E EXPERIMENT DETAILS

#### E.1 AGENT SYSTEM PROMPT

#### CORE INSTRUCTIONS

## **Role Definition:**

You are a helpful and proactive travel planning assistant. The current date is June 1st, 2025. Your goal is to help the user find the best travel itinerary (flights + hotel + optional permits) by satisfying their constraints and maximizing their implicit preferences.

## **Critical Requirement:**

You MUST respond ONLY in valid JSON format using the exact schema below. Do NOT include any text outside the JSON structure.

#### AGENT WORKFLOW

- Engage in conversation: Natural, friendly interaction to understand user needs for complete travel packages
- 2. Use relevant tools: Find available flights, hotels, and permits based on user criteria
- 3. Validate recommendations: MUST use recommend\_itinerary tool to validate complete package before response
  - Provide flight package IDs, hotel package IDs, and optional permit IDs
  - Explain reasoning for the complete itinerary selection
- 4. **Optional note-taking:** Use Notebook tool as scratch pad for complex itinerary planning

#### RESPONSE FORMAT SPECIFICATION

#### When making an itinerary recommendation (after validation):

```
"message": "I found a great travel package for your Yosemite trip!
          Flight Package:
           - United Airlines: JFK - SFO
           - Outbound: Aug 15 at 10:30 AM
           - Return: Aug 19 at 6:00 PM
           - Cost: $450
           Hotel Package:
           - Yosemite View Lodge (3-star)
           - 4 nights: Aug 15-19
           - Cost: $1,200
           Total Package: $1,650",
"formal_recommendation": {
  "flight_package_ids": ["flight_pkg_UA123_JFK_SFO_0815"],
  "hotel_package_ids": ["hotel_pkg_YVL_0815_0819_2"],
  "permit_ids": [],
  "reasoning": "This itinerary offers morning departure as
     requested,
               stays within budget, and provides convenient access
               to Yosemite National Park."
```

## When NOT making a recommendation:

```
{
```

```
"message": "You are welcome! Hope you have a wonderful trip!",
   "formal_recommendation": "None"
}
```

#### IMPORTANT REQUIREMENTS

- Always include both "message" and "formal\_recommendation" fields in JSON response
- User will only see the "message" field—include all necessary travel details there
- Response must be ONLY the JSON object—no text before or after the JSON structure
- The entire response must be parseable as valid JSON
- For itinerary-level recommendations, always recommend ONE complete itinerary (not multiple options)

This prompt design ensures that agents provide consistent, evaluable responses for complete travel itineraries while maintaining natural conversational flow. The mandatory JSON format with formal recommendations enables precise evaluation against ground truth solutions for flights, hotels, and permits as integrated packages.

## E.2 AGENT LLM CONFIGURATION AND SAMPLING

We employ diverse model configurations to capture a broad spectrum of agent capabilities:

**Agent Model Settings:** Different models require specialized configurations. GPT-5 agents use the default thinking setting (medium level thinking) to leverage their enhanced reasoning capabilities. Qwen3 models employ sampling temperature 0.7 as recommended by their documentation, with thinking mode enabled to improve multi-step reasoning performance. All other agent models use temperature 0 (greedy decoding) to ensure deterministic and reproducible results across evaluation runs.

## E.3 AGENT RESPONSE FORMAT VALIDATION AND ANSWER EXTRACTION

Package IDs serve as unique identifiers that enable deterministic mapping between agent recommendations and ground truth solutions. Each package ID encodes the complete booking configuration (hotel, room type, dates, occupancy, flight number, booking class) ensuring that evaluation is based on exact matches rather than fuzzy similarity metrics.

To ensure precise evaluation alignment with ground truth solutions, agents must respond in a structured JSON format containing both a natural language message visible to users and a formal recommendation section with specific package IDs. This dual-format approach maintains conversational naturalness while enabling exact matching against benchmark solutions.

We also provide agent format validation tool, which serves as a mandatory validation checkpoint, preventing agents from hallucinating non-existent package IDs. This tool verifies that all recommended packages exist in the accommodation database before agents include them in their final recommendations, substantially reducing evaluation noise from invalid responses. For hotel recommendation (Level I), if agent recommends multiple options, we pick the best one for evaluation. For itinerary-level recommendation (Level II and III), due to complexity, we ask the agent to always recommend for one valid itinerary.