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RESEARCH ARTICLE

Toward Interpretable and Persistent Personalization: A Memory-Augmented Agent Framework for LLM-Based Travel Planning

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ABSTRACT With the widespread application of large language models (LLMs) in intelligent conversation and recommender systems, integrating them into travel-related tasks has become a key research focus within the smart mobility domain. However, limitations such as high fine-tuning costs, cold-start challenges, issues in validation and logical coherence, and difficulties in maintaining contextual memory hinder the effectiveness of personalized interactions by traditional LLMs in travel scenarios. To address these challenges, we propose the Reasoning-enhanced Multi-turn Agent with Personalized Adaptation Framework (ReMAP), a generation-augmented agent framework that reduces personalization costs, improves validation and logical interpretability via Reasoning-and-Acting (ReAct) and Chain-of-Thought (CoT) prompting, and incorporates self-updating and retrieval mechanisms for factual memory to enhance the robustness of personalized generation in LLMs. The Tibet tourism-oriented personalized interaction agent system built upon this framework demonstrates strong performance in multiple-round, multi-group response experiments conducted under real-world travel scenarios. Experimental results show that ReMAP significantly outperforms baseline approaches in cold-start responsiveness (+10.51% personalization accuracy), itinerary feasibility (+12.38% pass rate), and long-term personalization consistency.

INDEX TERMS Agent, factual memory, generation-augmented, LLMs, personalized, ReAct and CoT, Tibet tourism.

I. INTRODUCTION

In recent years, Large Language Models (LLMs) have demonstrated significant potential in personalized recommendation and intelligent travel planning. However, fundamental challenges persist in long-term memory persistence, dynamic user modeling, and explainable decision-making. To address these issues, researchers have increasingly explored technical pathways that integrate structured memory architectures with modular causal reasoning mechanisms. Among them, Mem0 leverages its graph-enhanced component Mem0g to represent user attributes, preferences, and health status as nodes in a dynamically evolving knowledge graph linked by semantic relationships; this mechanism enables automatic generation of reasoning chains during memory updates, thereby forming an initial framework for causal graph modeling in personalized services. Building upon this foundation, the Memory-Assisted Personalized LLM (MAP) system further introduces hierarchical retrieval, incremental updating, and vectorized storage mechanisms, effectively enhancing contextual coherence and behavioral traceability across multi-turn interactions—reflecting a paradigm shift from "static memory" to "evolving memory".

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A distinct line of research constructs domain-specific tourism knowledge graphs, utilizing triple-based representations to model latent causal associations among "users—preferences—attractions," thereby enabling path-matching-driven personalized recommendations and providing structural support for applying causal reasoning in complex real-world scenarios. Concurrently, the TravelAgent system is designed with a modularly decoupled reasoning workflow that explicitly integrates user preferences, itinerary constraints, and environmental context variables, generating travel plans embedded with logical dependency structures and thus improving controllability and auditability of the outputs. Collectively, existing efforts have achieved notable progress in graph-structured memory modeling, causal dependency expression, modular reasoning chain design, and long-term context maintenance. These advances not only promote the transformation of recommendation systems from "explanation-free generative mode" to "transparent and interpretable reasoning mode," but also lay a methodological foundation for developing next-generation intelligent cultural and tourism agent systems featuring visualizable reasoning trajectories, traceable decision justifications, and extensible functional plugins.

Despite these advancements, however, traditional LLMs continue to face significant challenges in real-world travel scenarios [1]. While structured memory and modular reasoning offer promising directions, their practical deployment is often hindered by inefficiencies in personalized fine-tuning, high computational costs, and insufficient cold-start strategies—all of which directly compromise the effectiveness of personalized interactions [2], [3]. For instance, even advanced frameworks like those combining big data and AI, such as the hybrid recommendation approach proposed by Fararni et al., can alleviate cold-start issues only at the cost of requiring extensive domain-specific data for model adaptation, leading to high implementation overhead [4].

Although prompting techniques like Reasoning-and-Acting (ReAct) and Chain-of-Thought (CoT) demonstrate enhanced LLM reasoning in tasks such as general question answering and mathematical reasoning, their adaptability to travel guide generation—which involves multi-dimensional user preferences, real-time situational feedback, and long-term planning—remains suboptimal [5], [6], [7]. Xie et al. report that mainstream LLMs (e.g., Generative Pre-trained Transformer 4, GPT-4) achieve only a 0.6% success rate on complex travel queries with multiple constraints even with ReAct integration [8]. We argue that existing ReAct and CoT methods heavily rely on contextual reasoning, struggling to incorporate user-specific information (e.g., persistent preferences, historical behaviors). This results in outputs that fail to align with users' actual needs and weakens logical consistency when managing multi-associative constraints (e.g., budget control, time scheduling, dietary preferences) [9]. Thus, current prompting techniques are insufficient to support high-quality personalized generation in travel scenarios.

Furthermore, conventional LLMs' context-only memory mechanisms lack capacity for persistent behavior modeling and personalized trait extraction [10]. Travel recommendations require not only current dialogue context but also comprehensive multi-dimensional user profiling for decision-making [11], [12]. Since traditional LLMs lack systematic internal memory extraction and updating—even with external knowledge augmentation (e.g., Retrieval-Augmented Generation, RAG)—they cannot deliver truly user-profile-driven personalized experiences [13]. Notably, Tibet, as a culturally significant destination, attracts diverse travelers due to its high-altitude terrain, religious heritage, and intricate itineraries, further amplifying user preference heterogeneity [14].

To address these challenges and regional characteristics, we propose a Function-Calling-inspired generative enhancement framework [15], [16]. This agent architecture supports two distinct generation pathways—one for general question answering and one for strategic travel planning—to achieve flexibility, interpretability, and extensibility.

- Flexibility: Flexibility is reflected in the modular design with Function-Calling prompts, enabling rapid deployment, iterative updates, and seamless cross-platform migration [17].
- Interpretability: An integrated "Think–Act–Observe" ReAct pipeline for personalized travel planning, enhanced by CoT reasoning during the "Think" phase, ensures logical feasibility and traceability for debugging.
- Extensibility: Support for cross-scenario adaptability by enabling Self-Updating Vector Database, personalized user profiles, and scalable prompt templates.

We further introduce a multi-dimensional evaluation metric—A/B testing-based and covering accuracy, diversity, and user satisfaction—for agent personalization capabilities, validated through experiments in Tibet. Results demonstrate that our framework resolves LLMs' limitations in travel personalization while establishing a novel technical pathway toward building interpretable and scalable intelligent travel service systems.

II. METHODS

This paper highlights the need for customized tools in Agent framework experimentation to ensure system flexibility, portability, and extensibility. Below are the key technologies and their functions.

A. BASELINE MODEL

This study selects the Qwen-3 series of models—particularly Qwen3-235B-A22B—as the central component of the Agent framework. The model integrates two operational modes: a reasoning mode and a generation mode. The reasoning mode is designed for multi-step reasoning and logical decomposition in complex tasks, while the generation mode is optimized for contextual response generation and efficient text generation. This dual-mode architecture ensures that the model maintains logical consistency in reasoning-intensive scenarios while preserving fluency and low-latency responses in interactive settings, thereby supporting diverse travel-related tasks such as multi-constraint planning, long-text modeling, and personalized generation. The advantages of Qwen-3 go beyond the trade-off between reasoning and generation, exhibiting robust performance in long-context understanding, multilingual support, and knowledge generalization. In long-context processing, the model maintains semantic coherence across dialogue turns, reducing the risk of information loss and semantic drift. In multilingual adaptation, Qwen-3 improves system accessibility and functionality in international travel scenarios through cross-lingual modeling. For knowledge generalization, the integration of large-scale pretraining and instruction fine-tuning enables robust stability and adaptability across diverse domains. These characteristics position Qwen-3 not merely as a standard language generator, but as a core computational operator within the Agent framework, enabling robust and adaptive performance in complex, real-world task environments [18].

B. ReAct AND CoT COLLABORATIVE PROMPT METHOD

To further enhance the model's reasoning capability and decision transparency in complex task scenarios, this study employs an integrated prompting framework that combines Reasoning-and-Acting (ReAct) with Chain-of-Thought (CoT) [19]. This approach enables dynamic coupling between reasoning and interaction through an iterative ''Think–Act–Observe'' cycle. In the Thinking phase, the model decomposes task objectives using CoT and identifies feasible execution paths. In the Acting phase, the model performs actions based on the reasoning output and retrieves environmental feedback. In the Observation phase, the model integrates feedback to refine the reasoning chain and update subsequent plans. This mechanism not only improves the interpretability of the reasoning process but also provides the model with self-correction capabilities, enabling it to maintain logical coherence and goal alignment during task execution. Compared to traditional prompting techniques, ReAct and CoT offers two key advantages: first, the systematic decomposition of logical structure mitigates non-sequential reasoning and inconsistencies, thereby reducing the risk of logical conflicts; second, the incorporation of dynamic feedback enables the model to iteratively refine and optimize its reasoning path, enhancing both task success rate and execution stability. The methodology emphasizes a closed-loop design between reasoning and action, transforming large language models from generative systems into core components of interactive agents with reasoning and adaptive capabilities. In this study, ReAct and CoT is applied to the prompting architecture of the Travel Tips Processing Module, where its transparent reasoning process and iterative validation mechanism provide a reliable foundation for handling multi-dimensional constraints in complex scenarios. This approach not only strengthens the depth and robustness of model reasoning but also enhances the interpretability and extensibility of the Agent framework, making it better suited for deployment in high-complexity decision-making environments.

C. SELF-IMPROVING MEMORY LAYER MEM0 FOR AI AGENTS

To overcome the limitation of traditional Retrieval-Augmented Generation (RAG) [20], [21] methods—which are restricted to static knowledge retrieval—this study introduces and customizes the Mem0 self-improving memory layer, enabling dynamic extraction, storage, and updating of memory, thereby supporting continuous knowledge accumulation and refinement in long-term interactions. The Mem0 [22] architecture consists of two phases: the ''Extraction Phase'' and the ''Update Phase'', as illustrated in Fig. 1. In the ''Extraction Phase'', the system leverages large language models (LLMs) to extract key information requiring long-term retention from user inputs and historical context, and converts it into vector embeddings stored in the database; in the ''Update Phase'', the system compares new and existing memories based on semantic similarity and performs operations such as merging, replacing, or adding new entries via a Tool Call mechanism, enabling memory self-evolution. The database serves not only as the core storage component but also provides global semantic context during retrieval, thereby enhancing model grounding. In this study, Mem0 is used to construct the ''Fact Memory Processing Module'', supporting long-term user preference modeling and dynamic constraint management in travel tasks. During multi-turn dialogue, the system automatically identifies and extracts critical information, writes it into long-term memory, and retrieves it in subsequent interactions via semantic search, serving as a persistent reference for planning and recommendation. Furthermore, Mem0's update mechanism enables dynamic adjustment of stored information, ensuring the system adapts to evolving user needs while maintaining interaction consistency and reliability. Through this mechanism, Mem0 achieves continuous accumulation of long-term knowledge and enhances the system's coherence and flexibility in personalized recommendations and multi-turn interaction.

III. SYSTEM AND EXPERIMENTAL SECTION

A. ReMAP STRUCTURE

The Reasoning-enhanced Multi-turn Agent with Personalized Adaptation Framework (ReMAP) is a prompt-based agent architecture designed for travel scenarios, as illustrated in Fig. 2. By supporting interactive customization and modular composition through dynamic coordination among functional modules and closed-loop data flow, ReMAP enables end-to-end optimization of personalized travel dialogue generation. In the cold-start phase, the system initializes

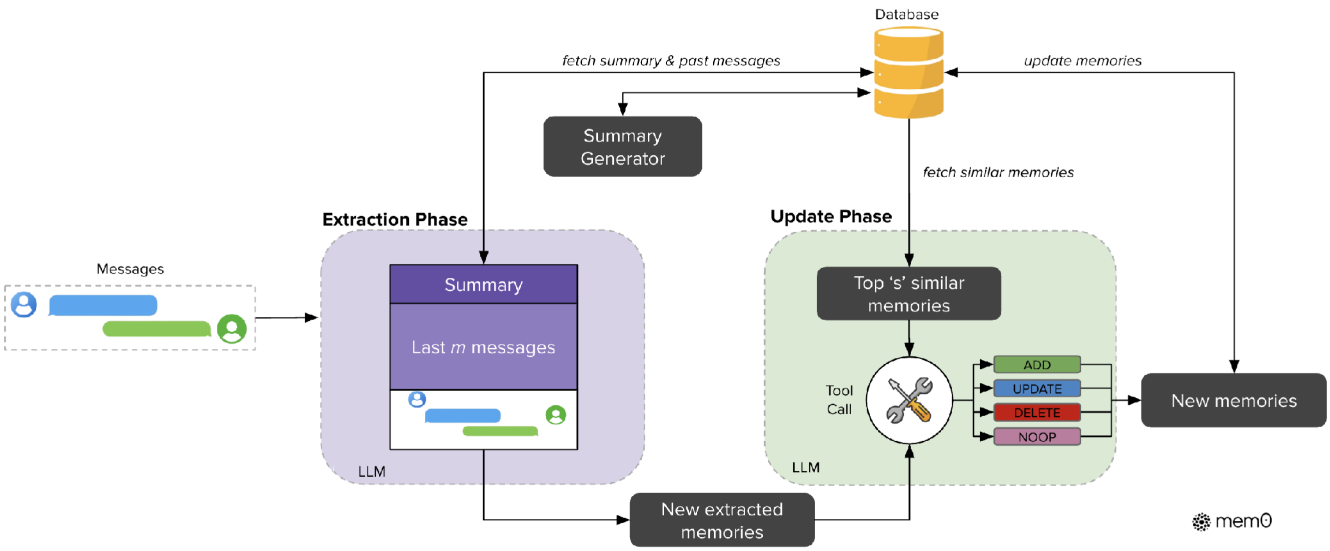

FIGURE 1. **System architecture diagram of Mem0.**

personalization using the central User Profile Database, which provides a static foundation for initial recommendations. This database dynamically interacts with the Factual Memory Processing Module throughout multi-turn conversations. The latter performs semantic aggregation and structured storage of both transient user needs and long-term preferences by extracting, labeling, and reranking soft and hard facts. Upon receiving a user query, the Travel Tips Processing Module first employs a requirement analyzer to determine the task type. For non-planning queries, the system directly retrieves relevant factual memories and integrates them with profile data into a unified prompt structure. For planning-intensive tasks, ReMAP deeply couples the "Think–Act–Observe" framework of Reasoning-and-Acting (ReAct) and Chain-of-Thought (CoT) reasoning within the factual memory system. Unlike standard ReAct, which relies on static predefined rules, or conventional CoT that follows a unidirectional linear inference path, our framework dynamically injects soft and hard facts—such as budget constraints and health risks—into the Observe phase. In the Think phase, it explicitly grounds personalized context through a CoT chain (e.g., "assessing travel pace $\rightarrow$ allocating budget $\rightarrow$ validating feasibility"), generating interpretable and traceable reasoning trajectories. In contrast to traditional ReAct implementations, where the "Think–Act–Observe" cycle lacks cross-session memory support—leading users to repeatedly state their preferences across different dialogues—ReMAP maintains persistent personalization via its structured memory layer. All aforementioned components are integrated through the Personalized Prompt Orchestration Framework, which synthesizes multi-source inputs—including user profiles, historical summaries, soft/hard facts, and real-time queries—to drive large language models (LLMs) in generating context-aware and situationally adaptive responses. Compared to existing research exploring graph-structured memory, causal dependencies, and modular reasoning chains, ReMAP advances further by ensuring systematic flexibility, interpretability, and extensibility in personalized travel planning agents.

1) USER PROFILE DATABASE

To mitigate the degradation of personalized recommendation capability in cold-start scenarios induced by sparse historical interaction data, we design and implement a User Profile Database to store core static user profile attributes — including age, gender, physical condition, travel duration, budget, attraction preferences, and companion information [23]. Serving as the initial anchor point for the personalized generation system, this database is collaboratively invoked by both the Travel Tips Processing Module and the Personalized Prompt Orchestration Framework, enabling the generation of preliminary personalized content during the cold-start phase. Concurrently, the Factual Memory Processing Module maintains the timeliness and consistency of the evolving user profile throughout extended multi-turn interactions via its dynamic update mechanism.

2) TRAVEL TIPS PROCESSING MODULE

This module comprises a travel guide requirement analyzer and a travel planning suggestion generator. The analyzer leverages an LLM to determine whether the user's query involves generating a travel guide, thereby triggering the corresponding feedback process.

The general feedback process is designed for non-planning, simple queries. When activated, the system redirects to the fact memory module for retrieval and integrates user profile data, basic user information, cache memory including the last N rounds of soft and hard facts, dialogue summaries, recent dialogue history, and the current query into a personalized prompt framework. The planning-specific

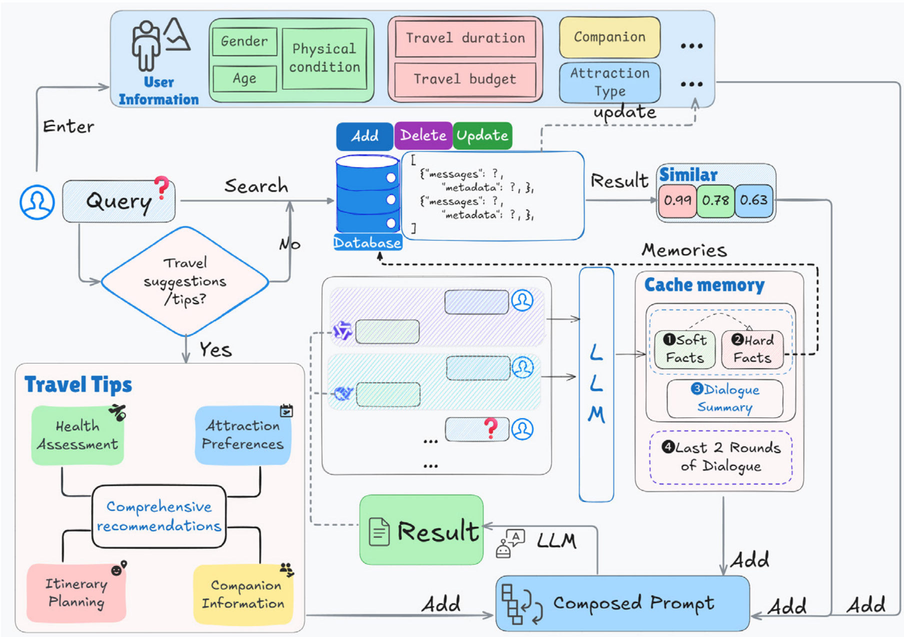

FIGURE 2. ReMAP structure diagram.

feedback process targets complex multi-constraint planning tasks. It invokes the suggestion generator to produce travel plans, which are then incorporated into the same prompt framework as the general process but with additional integration of the planning suggestions.

Based on the requirements analysis, the suggestion generator consists of four components: health assessment, itinerary planner, attraction preference analyzer, and companion information. Interaction rules and invocation logic are designed among these components to support selective calling and effective information fusion. Finally, an LLM is invoked to generate comprehensive and multi-dimensional travel suggestions.

To systematically delineate the modular architecture of the travel planning suggestion generator, this study performs a structured functional decomposition of each sub-module, explicitly specifying its input variables, core processing mechanism, and standardized output schema, as detailed in Table 1. This decomposition facilitates precise variable control and performance attribution analysis in subsequent experimental evaluations.

- Health Assessment: By integrating the user's basic information (e.g., gender, physical condition) with the Choquet integral for risk calculation and predefined risk classification rules, this component prompts the LLM to generate a personalized health risk assessment and corresponding recommendations [24]. The core computation is formulated as shown in Equation (1):

$$R = \sum_{i=1}^{3} (f_i - f_{i+1}) \cdot \nu(\{1, \dots, i\}), \quad i \in \{\text{age}, \text{gender}, \text{disease}\} \tag{1}$$

where R denotes the final risk score, ranging in [0, 1]; $f_{(i)}$ represents the univariate risk value. For each factor i, the model first estimates its likelihood of occurrence L_i and the severity of impact I_i, both taking values in [0, 1], yielding Equation(2):

$$f_{(i)} = L_i \cdot I_i \tag{2}$$

The values are sorted such that $f_{(1)} \geq f_{(2)} \geq f_{(3)} \geq 0$, and we set $f_{(4)} = 0$; $\nu(S)$ is the capacity function, used to measure the importance of subsets of risk factors.

- Itinerary Planner: Integrating user-specific inputs (e.g., travel duration, per capita budget), this study adopts the ReAct and CoT collaborative prompting framework, leveraging large language models (LLMs) to generate personalized travel itineraries. The planning module follows an "Act–Observe–Think" paradigm: in the Act phase, the overall travel objective is decomposed into executable subtasks such as attraction scheduling, transportation planning, accommodation selection, and dining arrangements; in the Observe phase, contextual factors including geographic structure, attraction distribution, local consumption levels, and lifestyle practices are incorporated to enrich reasoning and provide constraints; in the Think phase, CoT reasoning is applied under travel duration, budgetary, and preference conditions to progressively refine the itinerary. The CoT reasoning chain consists of the following steps: assessing travel pace → determining direction and maximum travel distance → recommending the number of attractions per day → defining travel style (e.g., meticulously planned, flexible, or balanced) → preparing necessary supplies → choosing transportation mode → selecting accommodation type and per-capita

TABLE 1. Functional architecture of sub-modules in the travel planning suggestion generator.

Sub-module Name	Input Variables	Core Processing Mechanism	Standardized Output
Health Assessment	Basic User Information(age, gender, physical condition,etc.)	Choquet integral for risk calculation and predefined risk classification	Personalized health risk assessment and recommendations
Itinerary Planner	travel duration, budget	ReAct and CoT collaborative prompting	Personalized itinerary plan
Attraction Preference Analyzer	attraction preferences	IRT-based implicit ranking prompting	Top-K attraction priority ranking
Travel Companion Information	companion information	Structured attribute encoding	Risk correction, special arrangements,etc.

cost → selecting dining options and per-capita cost → estimating total expenses → allocating overall budget. Through this integrated framework, the system produces feasible, user-tailored itineraries that balance efficiency, comfort, and safety.

- Attraction Preference Analyzer: This component integrates the user's basic information (e.g., preferred attraction types) with an implicit prompting method for attraction prioritization based on Item Response Theory (IRT) [25]. It guides users through preference selections across multiple scenarios, enabling the LLM to accurately rank their attraction preferences.
- Travel Companion Information: This component records the presence and count of vulnerable companions (e.g., elderly individuals, children, infants, persons with disabilities, and pregnant women) using numerical values and Boolean indicators [26].

3) FACTUAL MEMORY PROCESSING MODULE

We introduce the concept of soft/hard facts within the context of travel scenarios, and implement a fact extraction prompting module to extract these facts from user interactions. Based on Mem0's hierarchical labeling system, we develop a fact labeling prompting module that establishes an ordered storage structure and incorporates an automatic update mechanism for real-time knowledge refresh. Furthermore, by integrating Mem0's built-in keyword matching and semantic similarity reranking methods with our custom similarity score ranking approach, we design a three-level fact memory reranking framework to enable more efficient and accurate personalized matching [27], [28].

- Fact Extraction Module: Responsible for invoking the LLM to extract "hard facts" and "soft facts" from user interaction texts. Inspired by memory categorization in cognitive psychology, we classify user information into two types [29]: Hard facts refer to information that remains stable across multiple trips and does not easily change with specific contexts, reflecting a user's long-term characteristics or preferences (e.g., nationality, occupation, personality traits, enduring interests). These facts exhibit persistence across time and scenarios and can be reused in different travel tasks. Soft facts refer to temporary information related to a single trip or specific context, reflecting a user's immediate needs and dynamic intentions in the current scenario (e.g., budget, travel dates, destination, companions, temporary preferences). These facts are typically time-sensitive and valid only within a single dialogue session. Both soft and hard facts are dynamically updated during conversation turns. After each dialogue session, the hard facts from the current session are stored as factual memory text and made available for retrieval by the fact labeling prompting module.
- Fact Labeling Module: In the structured modeling of factual memory, this study proposes a Fact Labeling Prompt Component grounded in a two-tier "Category–Type" taxonomy. This component orchestrates the LLM to semantically categorize and hierarchically annotate factual memory texts extracted from user-agent interactions. Specifically, Category (primary class) represents a macro thematic domain, enabling first-level semantic clustering; Type (subclass) refines attribute granularity within each primary class, thereby supporting fine-grained personalization modeling. This architectural design achieves a dual objective: preserving semantic hierarchy clarity while ensuring system extensibility. When a novel fact resists mapping to existing subclasses, the LLM leverages its semantic induction capability to autonomously generate a new subclass label and dynamically update the taxonomy — facilitating the continuous, self-evolving nature of the knowledge structure. Tailored to the unique constraints of Tibet travel scenarios, the defined primary classes

TABLE 2. Taxonomy of travel-related factual memory labels.

Primary Class	Subclass Description
Demographic Information	Age, gender, occupation, etc.
Attraction Preference	Geographic features, activity types, seasons, etc.
Travel Style Preference	Pace, behavioral patterns, etc.
Accommodation Preference	Type, environment, service, location, etc.
Dining Preference	Cuisine type, dining context, ingredient sourcing, dietary restrictions, etc.
Transportation Preference	Travel tools, comfort level, speed, etc.
Health and Safety	Information related to physical condition, risk management, and altitude adaptation
Other Personal Preferences	Additional interests reflecting values, personality traits, or niche pursuits
Historical Background	Traveler's experience, competencies, cultural background, and key achievements

are anchored in core dimensions of user travel decision-making. Subclasses are meticulously configured according to localized factors — including high-altitude physiological adaptation, cultural-religious taboos, and infrastructural limitations (see Table 2) — to enhance context-sensitive memory retrieval and recommendation precision.

- Self-Updating Vector Database: The system is responsible for the structured storage of outputs from the fact extraction and labeling components. It distinguishes between *soft facts* and *hard facts*, represented by the sets S and H, respectively. Each soft fact is represented as a tuple $s_i = (\text{text}_i, t_i)$, where text_i denotes the fact text and t_i the timestamp. To facilitate temporal aggregation, each timestamp is mapped to a trip ID tid_i, representing the associated travel episode. For each text, a high-dimensional embedding vector v_i is computed, collected in the set V. Let τ denote the similarity threshold, k the length of the continuous trip window, and n the minimum occurrence threshold. The graph G is a similarity graph built on cosine similarity; its connected components are denoted as $C(G)$, each forming a cluster. For a cluster C, let $\text{trips}(C)$ denote the set of distinct trip IDs it contains. A hard fact is denoted as h, its embedding vector as v_h, and associated metadata includes attributes such as category and type [30]. Soft facts often represent only the original text snippet and its single occurrence timestamp, exhibiting transience and instability; without aggregation and verification, they are prone to redundancy or noise. By applying similarity-based clustering, time-window aggregation, and frequency-threshold constraints, multiple semantically similar, temporally continuous, and repeatedly occurring soft facts can be condensed into hard facts, effectively enhancing the stability and reliability of fact representation, thereby providing a more representative and authoritative foundation for subsequent knowledge storage, reasoning, and personalized generation. The complete update process is formally described in Algorithm 1.
- Retrieval Reranking Module: To improve the precision of personalized memory retrieval, the system invokes a LLM to extract metadata, specifically two semantic tiers (category and type), from user queries in a structured manner. This mechanism leverages semantic structuring to reduce the search space, enabling focused retrieval within a high-dimensional memory repository and thereby enhancing the semantic alignment between generated responses and user intent. The dual-layer category-type tagging system allows the system to capture user intent with greater fidelity and ensures high-fidelity matching between retrieved memory segments and the original query. Within the Mem0 memory architecture, the reranking (rerank) mechanism serves as a post-retrieval optimization module. It dynamically adjusts the ranking of candidate memory segments based on metadata extracted from the query. At its core, this process refines the initial retrieval results by incorporating dual weighting factors: semantic relevance and contextual recency. This achieves a fine-grained transition from "relevant" to "most relevant." Through dynamic parameter adjustment, the rerank mechanism flexibly personalizes the retrieval ranking according to varying query types and user contexts, including intent, constraints, and historical behavior. This improves the system's response accuracy and perceived user satisfaction. Its workflow consists of three core stages. First is structured metadata extraction, in which the system invokes a LLM to automatically extract key attributes—such as category and type—from the user input; this

Algorithm 1 Conversion of Soft Facts to Hard Facts Based on Time Clustering

Require: Soft fact set $S = \{s_i = (\text{text}_i, t_i)\}$, parameters k, n, τ
Ensure: Updated hard fact set H
Assign a trip id tid_i to each $s_i \in S$ based on its timestamp t_i
For each s_i, compute the text vector $v_i = \text{Enc}(\text{text}_i)$ and perform L_2 normalization; form the vector set $V = \{v_i\}$
Initialize an empty graph G (nodes are the indices i of each fact)
for all pairs (i, j) with $i < j$ **do**
  if $\cos(v_i, v_j) \geq \tau$ **then**
    Connect edge (i, j) in G
  end if
end for
Extract connected components from G to obtain the cluster set $C(G) = \{C_1, \ldots, C_m\}$
for all cluster $C \in C(G)$ **do**
  Let trips(C) = the ordered list of all tid_i within the cluster
  if there exists a continuous trip window of length k such that the number of distinct trips covered by the cluster $\geq n$ **then**
    Mark C as convertible
  end if
end for
for all cluster C marked as convertible **do**
  Aggregate the set of original sentences $\{\text{text}_m, \ldots, \text{text}_n\}$ within the cluster
  Use a large language model to summarize the above sentences and generate a formatted hard fact h
  Compute the hard fact vector $v_h = \text{Enc}(h)$ and perform L_2 normalization; construct metadata
  Write $(h, v_h, \text{metadata})$ into the hard fact set H
end for
return Updated H

structured metadata provides semantic guidance for downstream retrieval operations. Second is fact memory retrieval, which dynamically selects retrieval strategies based on a three-level prioritization mechanism, with retrieval recall serving as the trigger condition for priority escalation. At Priority Level 1, fine-grained retrieval is performed when full metadata (i.e., both category and type) is available, utilizing the internal Mem0 module to achieve high-precision semantic alignment. At Priority Level 2, if partial metadata is missing (e.g., type unspecified), the system defaults to coarse-grained retrieval based on category alone. If the first two levels fail to meet recall thresholds, the system proceeds to Priority Level 3 (Fallback), performing global semantic matching using the original user query to maximize recall under low-signal conditions. Finally, retrieval result reranking refines the initial results by combining semantic similarity scores and recency. This hybrid reranking strategy ensures that returned content is both highly relevant to user intent and temporally up-to-date, thereby significantly enhancing overall response quality and user experience.

4) PERSONALIZED PROMPT ORCHESTRATION FRAMEWORK

This framework constitutes an end-to-end prompt composition system for user-facing content generation. It selectively assembles multiple input sources—including basic user information, user profile memory retrieval results, travel planning suggestions, contextual dialogue cache (comprising N-turn soft/hard facts, N-turn summaries, and two-turn full dialogues), and current queries—according to scenario-specific requirements. The system executes multi-source fusion to yield context-aware generation outputs.

B. ReMAP-TIBET: A CUSTOMIZED SYSTEM FOR TIBET TRAVEL PLANNING

To evaluate the adaptability of ReMAP to complex real-world travel tasks, we have selected "Tibet travel" as a representative application scenario. On one hand, Tibet features a high-altitude environment, rich religious and cultural heritage, vast geospatial coverage, and heterogeneous user needs [31]. These characteristics offer a comprehensive evaluation of the agent's capabilities in cold-start response, user modeling, dynamic recommendation, and multi-constraint planning. On the other hand, Tibet travel imposes higher demands on the interpretability and personalized adaptation of generated content, making it an ideal testbed for assessing ReMAP's adaptability. Accordingly, building upon the original framework, we have adapted the Travel Guide Processing Module to better address the unique environmental and tourism-specific requirements of Tibet.

- Enhanced Health Risk Assessment Component: To mitigate potential health hazards inherent to Tibet's extreme high-altitude environment, this study integrates a clinically grounded risk assessment module into the agent's planning pipeline. The module systematically incorporates medical variables associated with Acute Mountain Sickness (AMS) and its common complications—including cardiovascular, chronic pulmonary, cerebrovascular, hematological, and upper respiratory conditions. Leveraging a Choquet integral-based aggregation model, it applies nonlinear weighting to these multidimensional indicators to derive personalized risk stratifications. This preemptive mechanism establishes a dynamic safety boundary for downstream itinerary generation, enabling the system to proactively filter out activities or routes that contravene the user's physiological constraints, thereby ensuring clinical plausibility and enhancing user safety in all generated recommendations.

- Localized Itinerary Planning: Acknowledging Tibet's unique geographical and infrastructural constraints—characterized by vast spatial scale, topographical heterogeneity, and sparse transportation networks—this study implements a domain-specific restructuring of the itinerary planner. The core strategy, termed segmented dynamic planning, decomposes the journey into geographically coherent subunits (e.g., Lhasa–Nyingchi–Ngari). Within each segment, Chain-of-Thought (CoT) reasoning is executed under the triple constraints of time, budget, and physical stamina, with outputs globally harmonized via a path coordination module. The system further incorporates localized consumption benchmarks and altitude-aware travel-time estimations to dynamically weight spatiotemporal costs. This architecture ensures planning feasibility and execution robustness by preventing itinerary fragmentation caused by excessive transit distances or resource misallocation, while maintaining strict adherence to user-defined constraints.
- Attraction preference analyzer refinement classification: To accurately model the multidimensional preference structures inherent to Tibet's heterogeneous tourism landscape, this study refines the semantic hierarchy of the attraction preference analyzer. Major scenic sites are categorized into three experiential typologies: natural landscapes (e.g., alpine lakes, glaciers), cultural heritage (e.g., ancient towns, intangible heritage workshops), and religious/spiritual sites (e.g., pilgrimage temples, kora trails). Guided by an Item Response Theory (IRT)-informed prompting mechanism, this granular classification enables the system to capture nuanced user preferences along these axes. By transforming implicit user feedback into structured preference rankings, the module significantly enhances the contextual relevance and semantic alignment of recommendation outputs, facilitating a transition from generic suggestions to truly personalized, experience-driven travel guidance.

These module-level enhancements significantly improve ReMAP's adaptability, stability, and decision transparency in high-risk, high-diversity tourism scenarios. To systematically evaluate the performance of ReMAP in the context of Tibet travel, we instantiate a specialized adaptation—ReMAP-Tibet—which serves as the unified experimental platform for three subsequent, independent evaluations: cold-start response, itinerary feasibility, and personalization effectiveness.

C. COLD-START RESPONSIVENESS ASSESSMENT

Intelligent travel systems—particularly those targeting specialized destinations like Tibet—face significant challenges due to a high proportion of first-time users and frequently unavailable historical behavioral data. To address this, the system must exhibit strong cold-start responsiveness. This section quantifies the system's capability to rapidly construct basic user profiles and generate actionable proto-personalized travel recommendations in the absence of historical interaction data.

1) EXPERIMENTAL DESIGN

To simulate realistic cold-start scenarios, we constructed a dataset comprising 70 synthetic user profiles and selected 10 representative samples from it. These samples encompass diverse age groups and gender combinations to reflect variations in travel demands across different demographics. Additionally, individuals are categorized by physical condition into high-risk and low-risk groups, enabling evaluation of the system's responsiveness in health-sensitive contexts. The dataset includes diverse trip durations (ranging from short-term to long-term) and budget levels (from low to high), enabling evaluation of the system's personalized recommendation performance under varying resource constraints. In terms of preferred attraction types, the profiles include a variety of categories—such as natural landscapes, cultural heritage sites, religious sites, and adventure activities—to enable direct validation of the system's capability to generate differentiated recommendations driven by user interests. Furthermore, companion information is structured to incorporate vulnerable populations—including elderly individuals, children, pregnant women, and persons with disabilities—ensuring that the experimental design accurately reflects the complexity inherent in diverse travel group compositions. The selected 10 samples not only represent the complexity inherent in cold-start conditions but also provide a basis for meaningful comparison with non-cold-start scenarios in controlled experiments.

Each profile includes only basic personal information. Based on this, the system generates initial itinerary proposals for major cities in Tibet. An LLM evaluator then scores the outputs against reference profiles using the following metrics.

- Personalization Accuracy: A key metric that evaluates whether the recommendation system effectively utilizes basic user information to improve the accuracy and relevance of recommendations. By analyzing the system's use of user profiles during the cold-start phase, this metric assesses whether incorporating basic user information improves the accuracy and relevance of recommendations, thereby reflecting the enhancement of the system's personalized service capability.
- Diversity: A key metric that measures the variety of recommendations generated by the system. It evaluates the breadth of geographic type coverage by computing the normalized information entropy of the attraction subtype frequencies, thereby reflecting the system's ability to generate comprehensive and spatially balanced travel itineraries.
- Geographical Distribution Index (GDI):GDI (Equation (3)) is a key metric that evaluates the balance between user preference alignment and scenario diversity in travel attraction recommendations. It assesses the breadth of geographic type coverage

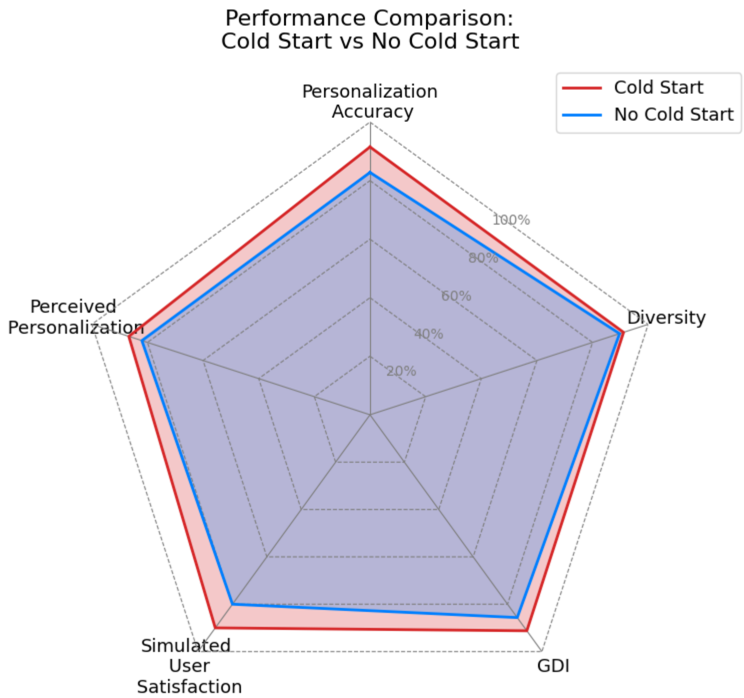

FIGURE 3. **Multi-dimensional performance improvement effect of cold start mechanism.**

by computing the information entropy of the attraction subtype frequencies, thereby verifying whether the system maintains both recommendation accuracy and diversity while avoiding homogenization. This metric reflects the system's ability to generate travel plans that cover diverse geographic types and provide diverse, engaging user experiences.

$$\mathrm{GDI} = \frac{2 \times \text{Personalization Accuracy} \times \text{Diversity}}{\text{Personalization Accuracy} + \text{Diversity}} \tag{3}$$

- Simulated User Satisfaction: A subjective metric that quantifies user-level satisfaction with the recommendations from the user's perspective, evaluating their overall acceptability and recognition in terms of user experience.
- Perceived Personalization Score: A key metric that assesses the perceived level of personalization in the recommendations. It evaluates whether the system enhances users' perception of personalized responses and the effectiveness of interaction guidance, thereby reflecting its ability to deliver tailored services aligned with individual needs and preferences.

2) EXPERIMENTAL RESULTS AND ANALYSIS

Fig. 3 presents a comparative analysis of evaluation metrics between cold-start and non-cold-start scenarios. Overall, the cold-start mechanism outperforms the non-cold-start baseline across all five core dimensions, demonstrating that the system can rapidly construct user profiles and generate rational recommendations based on basic user information, even in the absence of historical interaction data. Notably, in terms of personalization accuracy, the cold-start scenario achieves an average score of 91.51%, representing a 10.51% improvement over the non-cold-start scenario. This result indicates that user attributes effectively compensate for the lack of historical data in the initial phase, enabling the system to generate itinerary suggestions that are better aligned with individual needs.

The cold-start mechanism also exhibits advantages in diversity and GDI, with improvements of 1.59% and 6.52%, respectively. This suggests that, despite the absence of contextual interaction history, the system can still generate travel plans with broader coverage based on user profile knowledge, leading to more balanced geographical recommendations. However, the gains in these two metrics are relatively modest compared to personalization accuracy. This is likely because, in the early cold-start phase, the system prioritizes alignment with user information to ensure planning rationality and personalized matching, while its ability to expand diversity is constrained by the lack of historical dialogue context.

In metrics related to simulated user experience, the cold-start mechanism shows even more pronounced advantages. The simulated user satisfaction score reaches 90.00% in the cold-start scenario, a 12.5% increase over the non-cold-start scenario. This indicates that the travel plans generated by the cold-start mechanism are more consistent with user expectations, significantly enhancing user acceptance and trust in the system. Furthermore, the perceived personalization score is 86.70%, up by 5.73%, demonstrating that users can discern the difference in personalization quality between

FIGURE 4. **Feasibility assessment comparison of strategy processing module.**

the cold-start and non-cold-start conditions, even without a long interaction history.

In summary, the cold-start mechanism significantly improves system performance in the initial interaction phase by leveraging basic user information. It not only enhances the accuracy and rationality of travel planning but also substantially boosts user satisfaction and the perceived level of personalization. Although the improvements in diversity and geographical coverage are limited, this is primarily due to the system's emphasis on user-profile alignment and risk mitigation during the cold-start phase. Future work could further enhance the system's diversity and spatial coverage by integrating external knowledge bases or leveraging long-term interaction data, thereby achieving a broader recommendation scope and higher overall intelligence while maintaining strong personalized matching.

D. FEASIBILITY VALIDATION

This section systematically investigates how individual user constraints—such as travel duration, budget, physical condition, and travel preferences—affect travel plan generation, with particular emphasis on the practical executability challenges arising from inter-constraint conflicts. For instance, users may seek to visit premium attractions under budget constraints, or attempt extended treks despite limited physical capacity. Such conflicting objectives can render generated travel plans infeasible, thereby degrading the overall user experience. Consequently, adequately considering and balancing these personalized constraints during travel plan generation constitutes a critical step toward enhancing practical feasibility. This section systematically evaluates, via a controlled experiment based on four feasibility metrics, the impact of invoking versus not invoking the Travel Itinerary Processing Module — thereby empirically validating its efficacy in enhancing real-world executability. This section performs a systematic feasibility evaluation based on four evaluation dimensions, comparing systems with versus without the Travel Guide Processing Module, aiming to quantify its contribution to enhancing real-world feasibility.

1) EXPERIMENTAL DESIGN

We constructed four contrastive user profiles and produced itinerary proposals for a comprehensive planning task. The system generated outputs under two configurations: with versus without the travel itinerary processing module. An LLM evaluator assessed the results using a quadripartite scoring framework based on user profiles, yielding structured data for comparative analysis. The evaluation metrics included.

- Feasibility Pass Rate: A metric that measures the proportion of recommended itineraries that can be successfully executed under real-world constraints—such as user physical condition and companion composition—and is used to evaluate their practical feasibility.
- Information Completeness Score: A metric that evaluates whether the recommended itinerary covers essential travel elements—such as time scheduling, cost estimation, and necessary preparation items—ensuring the content is comprehensive and of high reference value.

- Simulated Human Evaluation Score: A subjective metric based on simulated user feedback, which evaluates the recommendations in terms of understandability, clarity of expression, and user-friendliness, thereby reflecting their interactive and presentational usability.
- Simulated Execution Score: A metric that quantifies the execution effectiveness of the recommended itinerary by evaluating its ability to resolve potential conflicts and adapt to complex situations, to assess the robustness and feasibility of the planning module in practical deployment.

2) EXPERIMENTAL RESULTS AND ANALYSIS

Fig. 4 compares the evaluation metrics of the system under four distinct user profiles, with and without the travel guide processing module enabled.

The feasibility pass rate increases by 12.38% when the module is active. This improvement indicates that the system, by integrating user-specific constraints—such as physical condition, companion types, and budget limits—can proactively avoid potential conflicts during itinerary generation, thereby enhancing the real-world executability of the travel plans.

Information completeness also sees a notable gain, rising by 14.17%. The generated travel guides now encompass not only basic schedules but also critical details like transportation modes, cost estimates, and risk advisories. In contrast, outputs from the system without the module, while structurally sound, often lack these essential details, leaving users to seek external information for practical use.

In the simulated human evaluation, the system with the module enabled achieves a 9.07% higher average score. This suggests that simulated users perceive these itineraries as more fluent, logically coherent, and usable. The system's ability to explain constraint violations and propose viable alternatives is particularly effective, thereby increasing user trust in the recommendations.

The simulated execution score shows the most significant improvement, rising by 12.60%. With the module, the system effectively mitigates common planning pitfalls—such as scheduling consecutive long-haul trips in high-altitude regions—by rationally allocating rest periods and offering low-cost alternatives when budgets are exceeded. This demonstrates that the travel guide processing module operates at both the strategic and operational levels, resolving real-world conflicts and producing recommendations that are truly actionable.

Overall, the system with the module enabled outperforms the baseline across all dimensions. This underscores the module's critical role: its structured conflict-resolution mechanism generates travel plans that are more comprehensive, coherent, and executable. As a result, user experience is improved, and the system's reliability in real-world applications is enhanced, directly addressing the practical feasibility of travel recommendations. Although the magnitude of improvement varies across user profiles, the consistent positive trend highlights the module's robustness and broad applicability. Future work could further boost feasibility in complex environments by integrating additional external knowledge bases and real-time user feedback.

E. PERSONALIZATION SYSTEM PERFORMANCE VERIFICATION

Personalized travel requires the integration of multiple sources of information, including user preferences, practical needs, and dialogue context. In Tibet travel scenarios, user preferences are often complex and subject to various constraints, placing higher demands on the system's understanding and adaptability. To address these challenges, the ReMAP-Tibet system introduces the Fact Memory Processing Module, which integrates the previous N-round dialogue summaries, soft/hard facts, and user profile memory retrieval into a structured prompt generation framework. This design aims to improve both the effectiveness of personalized generation and semantic coherence in continuous interactions.

1) EXPERIMENTAL DESIGN

To evaluate the personalized generation performance of the ReMAP-Tibet system, we designed five system versions as baseline configurations for comparative experiments, as shown in Table 3. The differences between versions primarily lie in the inclusion of structured modules and their integration into the prompt composition process.

Based on the four user profiles selected in Section III-D, we reverse-generated 100 questions (10 groups $\times$ 10 rounds) using Large Language Models (LLMs) for validation. We designed four sets of comparative experiments focusing on distinct core aspects to evaluate the contribution of each system component. For the first three experiments, responses were blindly evaluated by LLMs simulating human experts through standardized prompting and scoring protocols.

- System A vs. System B: Verify whether N-round dialogue summaries and soft/hard facts enhance contextual understanding and reasoning capabilities, assessed via task completion rate and reasoning soundness (10 random questions).
- System B vs. System C: Validate whether user profile memory retrieval improves personalized matching performance (10 questions, focusing on later rounds).
- System C vs. System E: Assess the impact of different retrieval methods on content richness, citation accuracy, and profile matching precision (10 questions, focusing on later rounds).
- System D vs. System E: Test whether dialogue summarization can preserve information integrity compared to full conversation history, measured by coherence-to-length ratio (i.e., similarity normalized by token count).

TABLE 3. System version configuration details and functionalities.

Version	Dialogue Summary	Soft / Hard Facts	User Profile Memory Retrieval
System A	×	×	×
System B	✓	✓	×
System C	✓	✓	✓ (Built-in)
System D	×	✓	✓
System E	✓	✓	✓

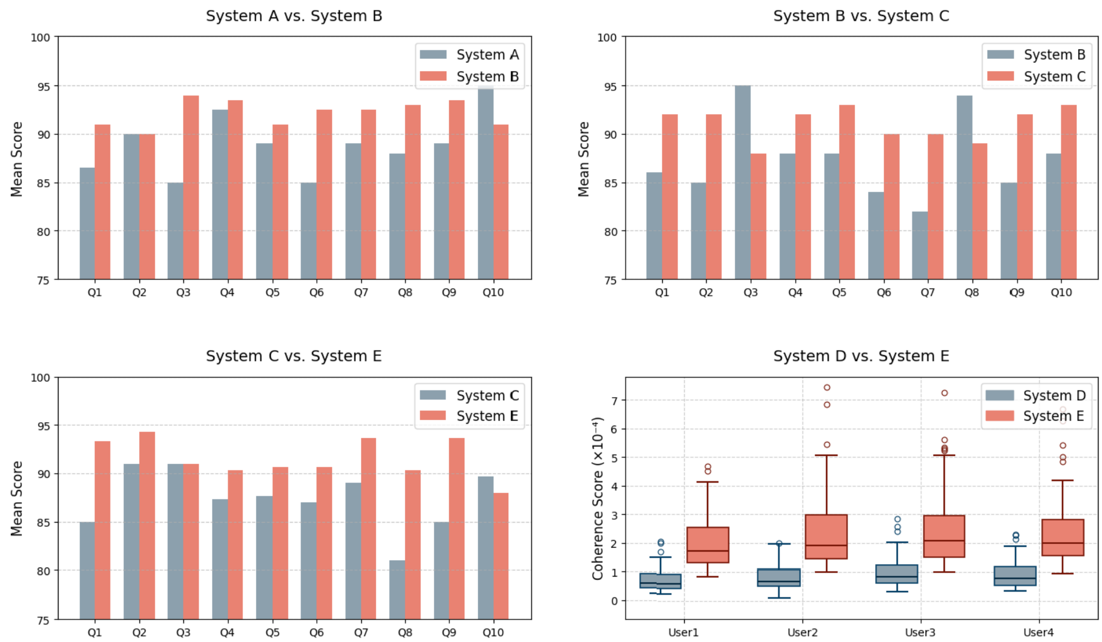

FIGURE 5. Comparative analysis of multi-module ablation in personalized system.

2) EXPERIMENTAL RESULTS AND ANALYSIS

Fig. 5 illustrates the performance differences among system versions based on four comparative experiments.

- System A vs. System B: System B achieves higher scores on 9 out of 10 questions, with an average improvement of 3.3 points. A closer analysis reveals that this advantage is not driven by a few extreme outliers inflating the mean, but rather stems from consistent small-to-moderate gains across the majority of test cases, with only a negligible number of instances showing reversed or tied performance. This performance distribution indicates that the integration of N-turn dialogue summaries and soft/hard facts exerts a broad positive impact across general scenarios: it mitigates information dilution caused by lengthy dialogues and enhances the availability of cross-turn critical information, thereby yielding robust improvements in requirement coverage and reasoning consistency.
- System B vs. System C: After incorporating user profile memory retrieval, System C outperforms System B on 8 out of 10 questions, with an average improvement of 3.6 points. In tasks requiring judgment and generation based on user dialogue preferences, personality traits, or individualized information, the additional contextual dimension provided by the user profile enables System C to generate responses that better align with user needs, demonstrating superior personalized matching performance. However, this advantage is not absolute; in a minority of cases, System B maintains comparable or slightly better performance. This observation indicates that the performance gain from user profile information is conditional: significant improvements occur when the profile is highly relevant to the query, whereas in scenarios with weak relevance, the profile contributes little to the reasoning process and may even introduce minor interference. Overall, the results of System C confirm the positive impact of user profile memory retrieval in most cases, yet highlight that its effectiveness is contingent upon the alignment between the query and the retrieved user profile.
- System C vs. System E: System E outperforms System C on 8 out of 10 questions, with an average improvement of 4.2 points. Comparative analysis reveals that E achieves higher citation accuracy and profile

matching precision across the majority of test cases, effectively raising the overall performance ceiling of the system. However, in a minority of instances, E fails to surpass C, indicating that while optimized retrieval strategies increase the likelihood of retrieving critical evidence, they also render the system more sensitive to retrieval parameters, ranking logic, and the quality of candidate passages. This heightened sensitivity leads to greater vulnerability to retrieval biases and the potential incorporation of irrelevant or noisy information. The coexistence of an elevated performance ceiling and reduced robustness reflects a typical capability-stability trade-off inherent in advanced retrieval-augmented generation architectures. This phenomenon suggests that future system designs should further strengthen retrieval fault tolerance and evidence filtering mechanisms to achieve synergistic optimization of high performance and high stability.

- System D vs. System E: System E achieves a higher overall median score, indicating superior performance in global logical coherence compared to System D. This advantage may stem from the dialogue summarization mechanism, which helps the model automatically filter out redundant information, thereby focusing attention on key contextual segments and facilitating the maintenance of content consistency and holistic coherence during reasoning and generation. However, although System E demonstrates better performance in terms of median score, its output exhibits greater variability, with a relatively higher number of outliers in the distribution. This suggests that generation quality is highly dependent on the quality of the summaries: when summaries are incomplete or poorly compressed, the model's outputs tend to deviate significantly. In contrast, System D employs full dialogue history as input, ensuring comprehensive information availability, which results in a more concentrated score distribution and higher overall stability. Nevertheless, this approach introduces substantial redundant context, increasing susceptibility to interference and making it difficult for the model to accurately capture the most salient semantics. Consequently, System D yields lower average performance and lacks the potential for high-impact, top-tier outputs.

IV. RESULTS AND DISCUSSION

The Reasoning-enhanced Multi-turn Agent with Personalized Adaptation Framework (ReMAP) demonstrates strong performance in experiments on personalized interactive agents for Tibet travel. In the cold-start responsiveness assessment, the system generates well-structured travel recommendations tailored to high-altitude travel requirements based solely on basic user information, significantly improving personalization accuracy, diversity, and simulated user satisfaction. The feasibility validation shows that, with the travel guide processing module enabled, the generated itineraries outperform the baseline (without the module) across key metrics—including feasibility pass rate, information completeness, and simulated execution score—particularly excelling in avoiding scheduling conflicts and ensuring resource accessibility. The personalized system performance evaluation further demonstrates that by integrating N-turn dialogue summaries, soft and hard facts, and user profile memory retrieval, the system substantially enhances personalized matching precision, requirement coverage, and reasoning validity in multi-turn interactions, while also improving contextual coherence and preference tracking. These results collectively demonstrate that ReMAP can rapidly generate high-quality, actionable, and personalized recommendations in complex travel scenarios.

Despite experimental results supporting ReMAP's strong performance in personalized generation and feasibility validation for Tibet travel tasks, its current version exhibits several structural limitations requiring systematic optimization in future iterations. First, under cold-start scenarios, while the system effectively adheres to high-altitude environmental constraints (e.g., altitude adaptability requirements, sensitivity to religious and cultural norms), the distribution of recommended points of interest (POIs) exhibits reduced information entropy. This indicates insufficient diversification capability when user profiles are sparse—a limitation stemming from the current reliance on static demographic attributes (e.g., age, occupation) for initial modeling, without incorporating active exploration mechanisms for latent interests. To enhance recommendation diversity during the cold-start phase, we propose integrating a Contextual Multi-Armed Bandit (CMAB) framework. In early dialogue turns, the system assigns dynamic exploration weights to each feasible POI category and, under hard constraints such as high-altitude safety and cultural compliance, probabilistically samples low-frequency yet valid categories. Explicit feedback or implicit behavioral signals from users serve as reward signals to update value estimates for each category, enabling gradual convergence toward a recommendation strategy that balances relevance and diversity. Additionally, during itinerary generation, Determinantal Point Processes (DPP) can be incorporated into the decoding process to explicitly promote semantic diversity among POIs, thereby reducing category redundancy from the outset. Second, the current dialogue summarization and compression mechanism lacks robustness in cases of missing context or semantic ambiguity, making it prone to reasoning chain fragmentation, which in turn weakens the semantic coherence and task alignment of generated content. This issue arises because the present approach relies on end-to-end large language model (LLM)-based compression without explicit structural constraints. We recommend introducing a schema-guided summarization framework that performs structured extraction based on predefined key fields—such as user goals, confirmed constraints, and pending clarifications—to improve the faithfulness and traceability of summaries. Third, the current factual memory module primarily models users' semantic memory but has not yet systematically integrated episodic or procedural memory. Particularly regarding episodic memory, the system has limited capacity to capture emotional feedback and contextual details from specific travel experiences. To address this, we propose constructing a structured "travel diary" architecture as a carrier for episodic memory. Each diary entry includes spatiotemporal context, activity type, emotional valence, and event outcomes. These entries are dynamically linked to the user profile via a lightweight memory retriever and automatically activated during multi-turn interactions when similar contexts arise. Furthermore, an event-driven memory update mechanism is proposed to handle abrupt shifts in user interests, replacing the current time-series clustering and threshold-based soft-to-hard fact conversion method, thereby enhancing the system's real-time adaptability. Finally, the cross-scenario transferability of ReMAP is currently constrained by its scenario coupling. Although Tibet-specific customization rules (e.g., health risk assessment for high altitude, tagging for religious sites) enhance task relevance, they necessitate significant reconstruction of prompt templates, tagging schemas, and constraint logic when migrating to heterogeneous scenarios such as island vacations or urban cultural tourism, resulting in high migration costs. This reveals an underdeveloped design at the "scene abstraction layer." Future efforts could draw upon modular ontology design principles, decoupling domain knowledge into pluggable "scene plugins" to enable configuration-driven migration.

V. CONCLUSION

Based on the Reasoning-enhanced Multi-turn Agent with Personalized Adaptation Framework (ReMAP), which integrates the ReAct and CoT prompting mechanism with factual memory processing, we have successfully developed a personalized interactive agent system for Tibet travel—ReMAP-Tibet. The system has been shown to outperform traditional LLMs in cold-start responsiveness, logical coherence, and personalized modeling. Benefiting from its modular design, ReMAP enhances system flexibility and interpretability, and supports rapid adaptation and functional extensibility across diverse travel scenarios. This architectural strength enables the agent to generate high-quality solutions for complex, multi-constrained travel requirements. This work not only demonstrates significant practical value in intelligent travel services but also provides methodological and technical foundations for the development of other personalized interaction systems.

Nonetheless, we acknowledge that ReMAP still has limitations in knowledge derivation and generalization capabilities. Future research will focus on three key directions: First, incorporating multimodal inputs (e.g., images, geospatial data, and real-time environmental signals) to enhance diversity and accuracy during the cold-start phase [32]. Second, integrating constraint-aware knowledge graphs with vision-language reasoning mechanisms to further improve logical consistency and contextual reasoning in complex itinerary planning. Third, constructing dynamic knowledge graphs and introducing adaptive fact transformation techniques to support real-time updating and iterative modeling of user profiles and preferences [33]. These enhancements aim to advance ReMAP in terms of intelligence, robustness, and scalability, laying a solid foundation for the development of next-generation personalized travel interaction agents.

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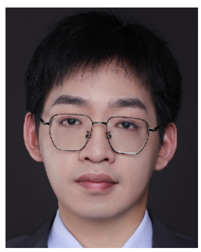

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