

Influence of hotel change frequency on the satisfaction of urban multiday personalized tourism itinerary

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ABSTRACT

In designing urban multiday personalized tourism itineraries, hotel selection and the frequency of hotel changes are key factors influencing tourists' satisfaction with the itinerary. To investigate the mechanism by which this factor affects itinerary satisfaction, this study proposes an urban personalized tourism itinerary design model that incorporates the frequency of hotel changes. A branch-and-bound algorithm is applied to obtain optimal tourism itineraries. Based on customer satisfaction theory, this study proposes a satisfaction evaluation model for personalized urban tourism itineraries across three dimensions: economy, convenience, and experience, and performs a satisfaction analysis of optimal tourism itineraries with varying hotel change frequencies. This study conducted case-based experiments using tourism data from Chongqing. The results indicate that personalized tourism itineraries based on a high-frequency hotel-change model outperform those of a low-frequency model across several indicators: average transportation costs decrease by ¥95, total distance travelled decreases by 47 km, and total rest time increases by 123 minutes. As luggage transfer services between hotels become more widespread, hotel selection and the frequency of hotel changes will have a greater impact on satisfaction with personalized urban tourism itineraries.



1. Introduction

Since the beginning of the 21st century, advances in information technology have strengthened the links between digital technologies and the cultural tourist industry.¹ Personalized urban tourism has gradually established itself as an essential choice for tourists.² Tourist are no longer satisfied with traditional, standardized tourism products, but are instead seeking itineraries that better match their individual preferences, encompassing multidimensional needs such as choice of attractions, accommodation, and transportation options. High-quality personalized urban tourism not only improves tourist satisfaction but also strengthens the emotional connection between

travelers and destinations, while promoting the sustainable development of the tourism industry.³

However, studies on tourist satisfaction indicate that it is influenced by a variety of factors, including attraction experiences, accommodation services, tourist activities, and environmental perceptions. However, current research often analyzes tourist satisfaction from the perspective of specific scenarios or individual factors, lacking a comprehensive examination of overall satisfaction with multiday itineraries. At the same time, existing research on the design of personalized urban travel itineraries has primarily focused on aspects such as attraction recommendations, optimization of visit sequences, and improvements in route efficiency.⁴ Yet, it has

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generally overlooked a key factor that directly impacts the visitor experience: the frequency of hotel changes. During urban multiday tourism, different frequencies of hotel changes lead to significant variations in itinerary satisfaction. In a low-frequency change model, tourists stay at a single hotel, avoiding the inconvenience and expense of luggage transfers associated with frequent moves. However, this can increase daily travel time if the hotel is located far from several attractions. Conversely, in a high-frequency hotel change model, travelers must use luggage transfer services and bear the associated moving costs, but they can change hotels several times depending on their travel itinerary. By choosing accommodations closer to the main tourist sites of the day, they can significantly reduce travel time between attractions and hotels, maximizing opportunities for sightseeing.

Therefore, scientifically determining hotel selection and the frequency of hotel changes while responding to tourist preferences and itinerary objectives has become a crucial research topic for improving tourist satisfaction during multiday urban tourism. In this context, this study develops a satisfaction evaluation model for personalized urban tourism itinerary based on the customer satisfaction theory,⁵ which encompasses three dimensions: economy, convenience, and

experience. On this basis, it proposes an optimized itinerary design model according to different hotel change frequency models. By solving this model using the branch-and-bound algorithm,⁶ the study examines the impact of hotel change frequency on satisfaction with tourist itineraries. The research approach is illustrated in **Figure 1**. This study aims to design efficient itineraries for urban multiday personalized tourism and improve tourist satisfaction.

The structure of this study is as follows: Section 2 reviews the literature on personalized tourist satisfaction in urban tourism and itinerary design. Section 3 proposes a satisfaction evaluation model for urban multiday personalized tourism itineraries. Section 4 develops optimization models for designing urban multiday personalized tourism itineraries that account for the frequency of hotel changes. Section 5 presents a case study to validate the effectiveness of the methodology. Section 6 summarizes the main conclusions and outlines future research directions.

The innovation of this study lies in the following aspects:

- (i) First, a more comprehensive model for evaluating satisfaction with urban multiday personalized tourism itineraries is proposed. This model not only incorporates the three

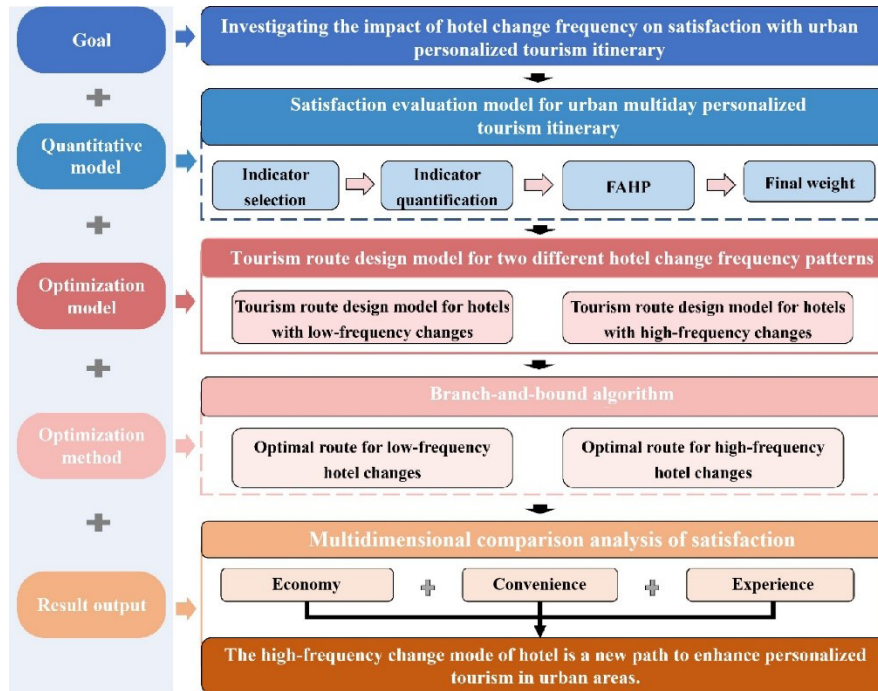


Figure 1. Research framework

Abbreviation: FAHP: Fuzzy analytic hierarchy process.

dimensions of economy, convenience, and experience based on customer satisfaction theory, but also employs the fuzzy analytic hierarchy process (FAHP) to quantitatively analyze the weights of different indicators.

- (ii) Second, an urban multiday personalized tourism itinerary optimization model that accounts for different hotel change frequencies was developed, and a branch-and-bound algorithm was designed to solve it; this model is capable of designing itineraries with higher satisfaction levels.
- (iii) Third, a comparative experiment on itineraries with different hotel change frequencies was conducted, revealing the mechanisms by which differing hotel change frequencies influence satisfaction with urban multiday personalized tourism itineraries.

2. Literature review

2.1. Urban personalized tourism considering tourist satisfaction

With the continuous development of the tourism market and the increasing diversification of consumer demands, urban personalized tourism has gradually emerged as a significant area of research in the tourism sector. As a key indicator for measuring the quality of urban personalized tourism experiences, tourist satisfaction has attracted significant attention from numerous scholars. Customer satisfaction theory⁵ is widely applied in tourism satisfaction research; this theory emphasizes that consumers form an overall satisfaction evaluation based on their actual experiences and multidimensional perceptions during the service process. Based on the above, existing literature in the field of tourist satisfaction research primarily focuses on two areas: the development of evaluation indicator systems and the analysis of influencing factors.

By focusing on evaluating tourist satisfaction, some researchers have established evaluation models. Shaykh-Baygloo⁷ used structural equation modeling to discover that the perceived quality of the attraction indirectly influences tourist satisfaction by affecting the sense of belonging to the place. Li *et al.*⁸ combined social representation and brand image transfer theories to construct a model using the Qingdao International Beer Festival as a case study, revealing the mechanisms by which direct experiences and social interactions influence the image of the event, the image of the city, satisfaction, and the intention to return. Su *et al.*⁹ validated for the first time, based on

the stereotypical content model, that the match between the linguistic style of service staff and the type of tourist activity influences satisfaction through the perception of cheerfulness and professionalism. Sun *et al.*¹⁰ employed multimodal big data and large language models to reveal that visual and auditory perceptions, aesthetic services, and convenience facilities are crucial to tourist satisfaction.

On the other hand, scholars have focused on identifying the various dimensions that influence tourist satisfaction in personalized urban tourism. Teixeira *et al.*¹¹ found that the quality of tourism activity planning significantly impacts satisfaction through aesthetic design and organizational arrangements. Ribeiro *et al.*¹² proposed that emotional connections between tourists and local residents—such as feeling welcomed and mutual understanding—indirectly enhance loyalty through tourist satisfaction. Tian and Hu¹³ employed spatial autocorrelation analysis, Geo-Detector, and location-weighted models to investigate location satisfaction patterns among 1,126 hotels in Wuhan. They found that proximity to highway exits, scenic accessibility, and free parking services exerted the strongest positive influence on spatial differentiation in hotel location satisfaction. Yang *et al.*¹⁴ demonstrated that tourists' sensory experiences with cuisine, service quality, and environmental ambience positively influence satisfaction and subjective well-being, significantly enhancing overall satisfaction. Guo *et al.*¹⁵ used text analysis, R programming, and entropy weighting to examine the relationship between landscape perception and tourist satisfaction. They found that tourist satisfaction largely corresponded to popularity, with visitors prioritizing landscape characteristics and environmental health while also appreciating accommodation and service management.

In summary, existing studies indicate that tourist satisfaction is influenced by various factors, including attraction experiences, accommodation services, tourism activities, and environmental perceptions. Otto and Ritchie¹⁶ pointed out that tourists' service experiences are multidimensional and gradually formed throughout the travel process. Similarly, Parasuraman *et al.*¹⁷ proposed that service quality is a multidimensional construct composed of several interrelated dimensions. A similar logic can be found in multi-criteria optimization research, where Aksu and Yaman¹⁸ generated Pareto-optimal design alternatives by considering multiple performance

criteria rather than relying on a single objective. These studies indicate that tourist satisfaction should be assessed from multiple perspectives rather than based on a single attribute. However, most existing studies analyze tourist satisfaction from the perspective of specific scenarios or individual factors, lacking a comprehensive examination of overall satisfaction with multiday tourism itineraries. Based on the above studies, this study further deconstructs tourist satisfaction with tourism itineraries into three quantifiable dimensions—economy, convenience, and experience—to provide an evaluation basis for the subsequent design of urban personalized tourism itineraries.

2.2. Design of urban personalized tourism itinerary

With the diversification of tourism demand and the rapid advancement of information technology, the design of urban personalized tourism itineraries has gradually become a hot topic of interest in both academic and industrial circles. Existing research primarily explores this field through optimization models and data-driven approaches.

Traditional optimization models approach tourism itinerary planning through mathematical modeling and heuristic algorithms. For example, Karagul and Gungor¹⁹ extended vehicle routing models to tourism applications by formulating a tourism-related routing problem as a heterogeneous fleet vehicle routing problem. Furthermore, Karagul *et al.*²⁰ proposed a 2-Opt-based evolution strategy for the travelling salesman problem, improving the efficiency of routing optimization. Paulavicius *et al.*²¹ innovatively proposed a hybrid greedy genetic algorithm. Using London as a case study, they provided 100% optimal solutions for large-scale itinerary planning while taking into account time constraints and personalized preferences. Sarkar and Majumder²² proposed the g-Tour algorithm, which infers tourists' interests from time allocation ratios. While balancing cost and satisfaction, it struggles to meet dynamically changing personalized demands. Vu *et al.*²³ proposed a branch-and-check approach for the tourist trip design problem with rich constraints, focusing on selecting feasible locations and constructing tourist routes under multiple constraints. Marzal and Sebastia²⁴ developed an incremental local search method for the tourist trip design problem with time windows and variable profits, aiming to improve route quality and computational efficiency. Sohrabi *et al.*²⁵

proposed an ant colony system algorithm for the orienteering problem with hotel selection to identify feasible intermediate hotels and optimize multiday routes. Sun *et al.*²⁶ introduced a multi-itinerary planning model based on matrix differential evolution algorithms, which effectively solves multi-itinerary planning problems through a classification of soft and hard constraints.

Data-driven approaches enable personalized recommendations by leveraging user behavior data and information from social networks. Cai *et al.*²⁷ used geolocated photos to build sequences of frequent attractions, generating itineraries by integrating spatiotemporal factors, but failed to solve the problem of daytime segmentation for multiday itineraries. Orabi *et al.*²⁸ developed the dual Tour-PIE-RO/RC algorithm by integrating real-time data from social networks with static information on points of interest, providing tourists with dynamic itinerary solutions that balance cost-effectiveness and personalized experiences. Liang *et al.*²⁹ innovated by integrating UGC text mining with fuzzy tag matching algorithms. Through dual-factor optimization of "information entropy weight + travel time," they significantly improved travel itinerary personalization and user experience value. Xu *et al.*³⁰ proposed a framework for merging data from multiple sources. Based on travel log data, review data, basic attraction information from tourism websites, and traffic data from online maps, they introduced a multiday itinerary recommendation framework that significantly improved recommendation accuracy, although it relies on the completeness of historical user data. Ataei *et al.*³¹ developed an integrated text-mining optimization framework for multiday tourist planning with hotel selection, in which review data were used to evaluate hotel-related aspects and support route optimization.

In summary, existing research has yielded substantial results in areas such as itinerary optimization algorithms, personalized recommendations, and multi-source data fusion, providing an important theoretical and methodological foundation for the design of urban personalized itineraries. However, as shown in **Table 1**, most existing studies treat accommodation as a fixed condition or a simple constraint, with research primarily focused on attraction recommendations, visit sequences, and itinerary optimization. This static treatment overlooks the potential role of accommodation changes in multiday tourism. Evirgen³² introduced a dynamic approach for constrained optimization

problems. Drawing on this dynamic optimization idea, this study further incorporates hotel change frequency into the model for designing urban personalized tourism itineraries and regards hotels not merely as departure or return points, but as service nodes that may change with daily itinerary arrangements. Additionally, by establishing two scenarios—low-frequency and high-frequency hotel changes—we analyze tourism itinerary satisfaction under different hotel change frequencies.

Table 1. Comparison of static and dynamic hotel models in tourism itinerary design

Related literature	No hotel	Static hotel	Dynamic hotel
Karagul and Gungor ¹⁹		✓	
Karagul <i>et al.</i> ²⁰	✓		
Paulavicius <i>et al.</i> ²¹	✓		
Sarkar and Majumder ²²	✓		
Vu <i>et al.</i> ²³		✓	
Marzal and Sebastia ²⁴		✓	
Sohrabi <i>et al.</i> ²⁵			✓
Sun <i>et al.</i> ²⁶	✓		
Cai <i>et al.</i> ²⁷	✓		
Orabi <i>et al.</i> ²⁸	✓		
Liang <i>et al.</i> ²⁹	✓		
Xu <i>et al.</i> ³⁰	✓		
Ataei <i>et al.</i> ³¹			✓
This study		✓	✓

3. Satisfaction evaluation model for urban multiday personalized tourism itinerary

This study constructed a satisfaction evaluation model for personalized urban tourism itinerary based on customer satisfaction theory. By quantifying tourists' overall perceptions of itinerary design during multiday urban tourism, the model transforms the abstract concept of "tourist satisfaction" into measurable indicators, providing a scientific basis for evaluating tourist satisfaction with personalized urban tourism itinerary. The mathematical symbols and their

descriptions used in this study are shown in **Table 2**.

Table 2. Symbol definitions

Variables	Definition
Set	
S	Set of hotels in the urban area, $S = \{1, \dots, s\}$
N	Set of attractions in the urban area, $N = \{s + 1, \dots, s + n\}$
V	Set of vertices in the urban area, $V = S \cup N$
Parameter	
T_l	Sightseeing time for tourists at vertex l , $l \in V$ and $T_l = 0, \forall l = 1, \dots, s$
c_{kl}	Time taken from vertex k to vertex l , $(k, l) \in V$
C	Total duration of the daily itinerary
m	Number of days in the tour
F_l	Ticket fee for attraction point l , $l \in N$
T_{kl}	The transport fare from vertex k to vertex l , $(k, l) \in V$
F_s	Daily fee for hotel s , $s \in S$
d_{kl}	Distance from vertex k to vertex l , $(k, l) \in V$
A_l	Tourist preference score of attraction point l , $l \in N$
R_s	Tourist preference score of hotel s , $s \in S$
Decision variables	
x_{kld}	0/1 variable, in the d th day trip, if vertex l is visited after visiting vertex k , $x_{kld} = 1$, otherwise, 0, $d \in (1, \dots, m)$; $(k, l) \in V$
u_k	Continuous variable, location of vertex k within a day's trip

3.1. Indicator selection for the satisfaction evaluation model of tourism itinerary

The satisfaction evaluation model for tourism itinerary primarily operates across three layers: the objective layer (A), the criterion layer (B),

and the indicator layer (C). The objective layer A focuses on travel itinerary satisfaction, while the criterion layer B examines three dimensions—economy (B_1),³³ convenience (B_2)³⁴ and experience (B_3)³⁵—further subdivided into nine specific indicator layers (C). As illustrated in **Table 3** and **Figure 2**, economic focuses on total ticket cost (C_{11}),³⁶ total hotel cost (C_{12})³⁷ and total commuting costs (C_{13}),³⁸ convenience involves total travel distance (C_{21}),³⁸ distance from hotel to attraction (C_{22}) and distance from attractions back to hotel (C_{23}); while experience encompasses total attraction score (C_{31}),³⁹ total hotel score (C_{32})⁴⁰ and total rest duration (C_{33}). Overall, the travel itinerary evaluation system comprises three levels and nine indicators. These criteria and metrics collectively form a multidimensional assessment framework designed to evaluate and optimize the planning and design of tourism itineraries.

Table 3. The satisfaction evaluation model for tourism itinerary

The objective layer (A)	The criterion layer (B)	The indicator layer (C)
Satisfaction with urban personalized tourism itinerary	Economy (B_1)	Total ticket cost (C_{11})
		Total hotel cost (C_{12})
		Total commuting cost (C_{13})
	Convenience (B_2)	Total travel distance (C_{21})
		Distance from hotel to attraction (C_{22})
		Distance from attractions back to hotel (C_{23})
	Experience (B_3)	Total attraction score (C_{31})
		Total hotel score (C_{32})
		Total rest duration (C_{33})

3.2. Quantitative method of indicators for the satisfaction evaluation model of tourism itinerary

The specific calculation formulas and definitions for each indicator in the satisfaction evaluation

model for tourism itinerary are detailed in **Table 4**.

3.3. Evaluation system for the tourism itinerary satisfaction model

Tourist satisfaction with urban personalized tourism itineraries is a multidimensional concept involving economy, convenience, and experience. Evaluating the relative importance of these dimensions relies heavily on tourists' subjective perceptions and preferences. Moreover, significant heterogeneity among tourists makes it difficult to obtain precise quantitative judgments regarding the importance of different evaluation criteria.⁴¹ Maretto *et al.*⁴² applied fuzzy logic and AHP-based frameworks to support the evaluation and selection of alternatives under multiple criteria. Paksoy *et al.*⁴³ employed fuzzy AHP and hierarchical fuzzy TOPSIS to evaluate alternative organizational strategies under multiple criteria. In addition, Erdebilli and Weber⁴⁴ discussed fuzzy multi-criteria decision-making methods for handling evaluation problems involving uncertainty and multiple criteria. Accordingly, this study employs the FAHP⁴⁵ to construct an evaluation index system for assessing tourist satisfaction with itineraries and to determine the weights of each indicator. FAHP effectively addresses the fuzziness and uncertainty inherent in tourist evaluations, as depicted in the flowchart in **Figure 3**. The steps for calculating indicator weights using FAHP are as follows.

First, a fuzzy complementary judgment matrix was constructed to evaluate indicators of satisfaction with tourism itineraries. For elements within the same level, pairwise comparisons of relative importance were made using elements from the preceding level as criteria, scoring them according to the 0.1–0.9 scale method shown in **Table 5**. When the score $r_{ij} = 0.5$, it indicates that indicator i and indicator j are equally important; when $r_{ij} > 0.5$, it indicates that indicator i is more important than indicator j , with a higher value signifying greater importance; when $r_{ij} < 0.5$, it indicates that indicator i is less important than indicator j , with a lower value signifying lesser importance.

Second, **Equation 1** provides the weight vector $W = (W_1, W_2, \dots, W_i, \dots, W_n)$ for the fuzzy complementarity judgment matrix, expressed as follows:⁴⁶

$$W_i = \frac{\sum_{j=1}^n r_{ij} + \frac{n}{2} - 1}{n(n-1)} \quad (1)$$

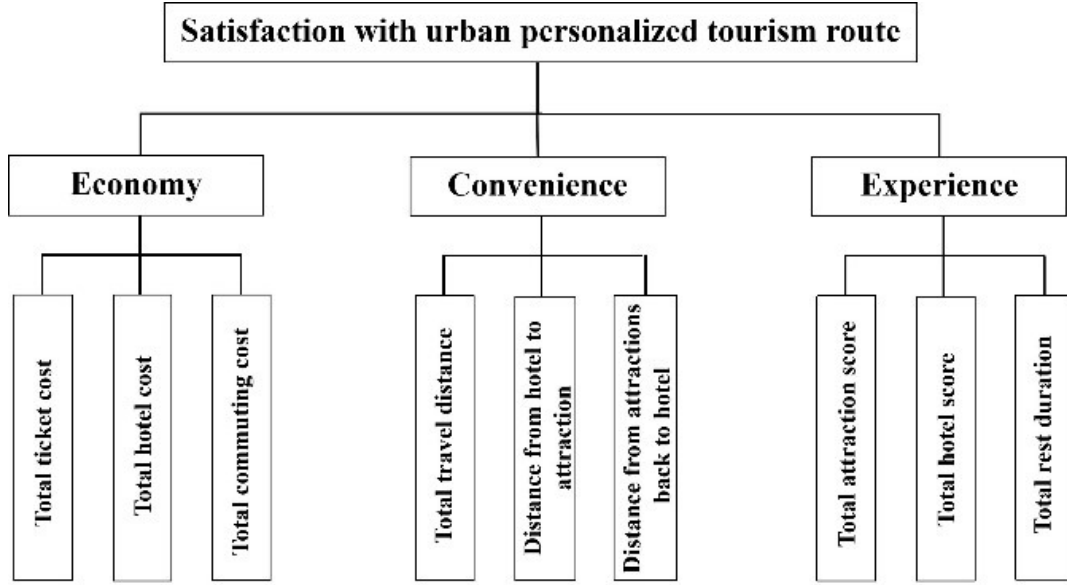


Figure 2. Evaluation indicators for tourism itinerary satisfaction

Table 4. Indicator definitions

The indicator layer	Formula	Definition
Total ticket cost (C_{11})	$C_{11} = \sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=1}^{s+n} F_l x_{kld}$	The total amount of admission fees actually paid by tourists for different attractions visited each day
Total hotel cost (C_{12})	$C_{12} = \sum_{d=1}^m \sum_{k=s+1}^{s+n} \sum_{l=1}^s F_s x_{kld}$	The total cost of hotel stays for tourists each day
Total commuting cost (C_{13})	$C_{13} = \sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=1}^{s+n} F_{kl} x_{kld}$	The total transportation costs incurred by tourists each day when traveling between attractions, and between attractions and hotel
Total travel distance (C_{21})	$C_{21} = \sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=1}^{s+n} d_{kl} x_{kld}$	The cumulative total distance traveled daily by tourists commuting between different attractions, as well as between attractions and hotel
Distance from hotel to attraction (C_{22})	$C_{22} = \sum_{d=1}^m \sum_{k=1}^s \sum_{l=s+1}^{s+n} d_{kl} x_{kld}$	The average daily commute distance for tourists traveling from the hotel to the first attraction
Distance from attractions back to hotel (C_{23})	$C_{23} = \sum_{d=1}^m \sum_{k=s+1}^{s+n} \sum_{l=1}^s d_{kl} x_{kld}$	The average commute distance from the last attraction visited each day back to the hotel
Total attraction score (C_{31})	$C_{31} = \frac{\sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=s+1}^{s+n} A_l x_{kld}}{\sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=s+1}^{s+n} x_{kld}}$	The average score for all attractions visited by tourists
Total hotel score (C_{32})	$C_{32} = \frac{\sum_{d=1}^m \sum_{k=s+1}^{s+n} \sum_{l=1}^s R_s x_{kld}}{m-1}$	Average score of hotels where tourists stay each day during their trip
Total rest duration (C_{33})	$C_{33} = mC - \sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=1}^{s+n} (c_{kl} + T_1) x_{kld}$	Total rest duration available to tourists after subtracting commuting duration and sightseeing duration from their total daily travel duration

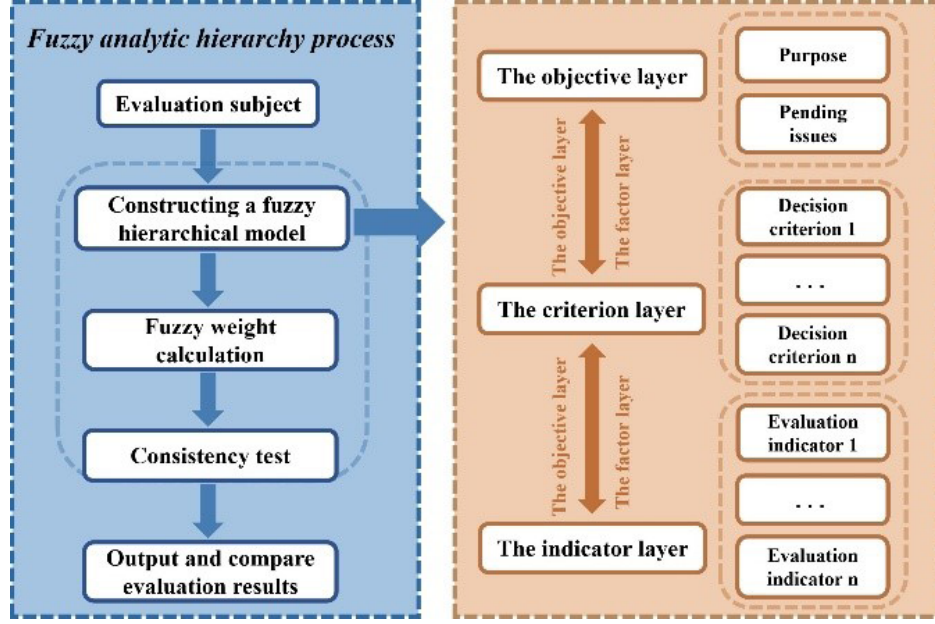


Figure 3. Flowchart of the fuzzy analytic hierarchy process

Table 5. Definition of judgment matrix scaling

Scale	Definition	Description
0.5	Equally important	When comparing the two factors, they are equally important
0.6	Slightly more important	When comparing the two factors, the former is slightly more important than the latter
0.7	Significantly more important	When comparing the two factors, the former is clearly more important than the latter
0.8	Strongly more important	When comparing the two factors, the former is significantly more important than the latter
0.9	Extremely more important	When comparing the two factors, the former is far more critical than the latter
0.1, 0.2 0.3, 0.4	Reverse comparison	If comparing factor a_i with a_j yields a judgment of $r_{ij} = 0.6$, then comparing factor a_j with a_i yields a judgment of $r_{ji} = 1 - r_{ij} = 0.4$

Finally, the consistency test was performed by calculating the characteristic matrix, using **Equation 2**. Fuzzy consistency was verified using the compatibility consistency ratio (CR) index. If $CR < 0.1$, the test is considered passed; otherwise, it fails. The CR index was computed using the fuzzy complementarity matrix and the characteristic matrix, as given by **Equation 3**.

$$W_{ij} = \frac{W_i}{W_i + W_j} \quad (2)$$

$$CR = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n |r_{ij} + W_{ij} - 1| \quad (3)$$

This paper only describes the determination process at the criterion level. The indicator level can be derived using the same method. Constructing the fuzzy complementarity between the target level A and the criterion level B, the determination matrix R_{A-B} is:

$$R_{A-B} = \begin{pmatrix} 0.5 & 0.4 & 0.3 \\ 0.6 & 0.5 & 0.4 \\ 0.7 & 0.6 & 0.5 \end{pmatrix}$$

The weight vector $W_{(A-B)}$ for the first-level indicator layer was calculated according to

Equation 1:

$$W_{(A-B)} = (0.284, 0.333, 0.383)$$

The feature matrix W_{A-B}^* was calculated using

Equation 2:

$$W_{A-B}^* = \begin{pmatrix} 0.5 & 0.4595 & 0.4250 \\ 0.5405 & 0.5 & 0.4651 \\ 0.5750 & 0.5349 & 0.5 \end{pmatrix}$$

Finally, the compatibility between the judgment matrix and the characteristic matrix was calculated. According to **Equation 3**, the compatibility between the judgment matrix and the characteristic matrix is $CR_{A-B} = 0.023 < 0.1$. The consistency test passes, indicating reliable results.

By repeating the above steps sequentially, the weight vector and compatibility of indicator layer C relative to criterion layer B are obtained as follows:

$$W_{B_1-C} = (0.367, 0.32, 0.313), CR_{B_1-C} = 0.0315 < 0.1;$$

$$W_{B_2-C} = (0.383, 0.30, 0.317), CR_{B_2-C} = 0.0506 < 0.1;$$

$$W_{B_3-C} = (0.357, 0.308, 0.335), CR_{B_3-C} = 0.0261 < 0.1.$$

The final ownership weight vector for travel itinerary satisfaction is shown in **Table 6**.

4. Optimization model for tourism itinerary design considering different hotel change frequencies

Designing urban personalized tourism itineraries involves multiple factors, including selection of points of interest,⁴⁷ travel time constraints,⁴⁸ hotel choices,⁴⁹ and itinerary optimization.³⁰ Efficient itineraries not only enhance visitor satisfaction but also effectively reduce travel costs while improving time utilization and comfort.⁵⁰ This section introduces mathematical models for low-frequency and high-frequency hotel changes. **Table 1** presents the mathematical symbols used in this study and their descriptions. In this model, V denotes the vertex set comprising two

Table 6. Final weightings of the evaluation system

The objective layer (A)	The criterion layer (B)	Criterion weighting	The indicator layer (C)	Indicator weighting	Synthetic weight
Satisfaction with urban personalized tourism itinerary	Economy (B_1)	0.284	Total ticket cost (C_{11})	0.367	0.104
			Total hotel cost (C_{12})	0.32	0.09
			Total commuting cost (C_{13})	0.313	0.089
	Convenience (B_2)	0.333	Total travel distance (C_{21})	0.383	0.128
			Distance from hotel to attraction (C_{22})	0.30	0.10
			Distance from attractions back to hotel (C_{23})	0.317	0.106
	Experience (B_3)	0.383	Total attraction score (C_{31})	0.357	0.137
			Total hotel score (C_{32})	0.308	0.118
			Total rest duration (C_{33})	0.335	0.128

types of vertices: hotels ($S = \{1, 2, \dots, s\}$) and points of interest ($N = \{s+1, s+2, \dots, s+n\}$). Furthermore, if a tourist travels from point k to point l on day d , then $x_{kld} = 1$; otherwise, it is 0. Sections 4.1 and 4.2 outline the objectives and constraints of the different models, respectively.

4.1. Tourism itinerary design model for hotels considering low-frequency changes

4.1.1. Model assumption

In the low-frequency itinerary design model for hotels, travelers stay in the same hotel for the entire duration of their trip to minimize the inconvenience and costs associated with changing accommodations. This model is based on the following assumptions:

Fixed accommodation principle: travelers prefer to stay in the same place for the entire duration of their trip, avoiding frequent changes to prioritize stability and comfort.

4.1.2. Objective function

The objective function represents the minimization of total travel time. Specifically, it optimizes the routes from the hotel to attractions and between attractions across all days to achieve the shortest total travel time, thereby allowing tourists to enjoy more rest time, as expressed in **Equation 4**:

$$\text{MinC} = \sum_{d=1}^m \sum_{k=1}^{s+n} \sum_{l=1}^{s+n} x_{kld} (c_{kl} + T_l) \quad (4)$$

4.1.3. Constraints

Constraint 5 ensures that tourists depart from and return to the same hotel on the first day of the itinerary. **Constraint 6** ensures that tourists depart from and return to the same hotel on the final day of the itinerary, thereby guaranteeing the itinerary's completeness and closed-loop nature. **Constraints 7** and **8** further ensure that each day's itinerary begins and ends at a hotel, thereby guaranteeing the rationality of accommodation arrangements. **Constraint 9** stipulates that the hotel where tourists stay each night serves as the starting point for the next day's itinerary, ensuring continuity and convenience. **Constraint 10** aims to guarantee that tourists return to the same hotel each day. **Constraint 11** ensures every attraction is visited, preventing omissions of key tourist sites and enhancing the visitor experience. **Constraint 12** ensures that the next attraction or hotel begins immediately after each attraction concludes. **Constraint 13** limits daily

travel time to a reasonable budget, preventing overly packed schedules or fatigue. **Constraint 14** ensures itinerary coherence by eliminating subloops, avoiding unnecessary redundant paths or isolated loops, thereby optimizing itinerary feasibility

$$\sum_{k=1}^{s+n} x_{hkl} = \sum_{l=1}^{s+n} x_{lhl} \quad \forall h \in \{1, \dots, s\} \quad (5)$$

$$\sum_{k=1}^{s+n} x_{hkm} = \sum_{l=1}^{s+n} x_{lhm} \quad \forall h \in \{1, \dots, s\} \quad (6)$$

$$\sum_{l=1}^s \sum_{k=1}^{s+n} x_{kld} = 1 \quad \forall d \in \{1, \dots, m\} \quad (7)$$

$$\sum_{k=1}^s \sum_{l=1}^{s+n} x_{kld} = 1 \quad \forall d \in \{1, \dots, m\} \quad (8)$$

$$\sum_{k=1}^{s+n} x_{khd} = \sum_{l=1}^{s+n} x_{hl(d+1)} \quad \begin{matrix} m \geq 2; \forall d \in \{1, \dots, m-1\}; \\ \forall h \in \{1, \dots, s\} \end{matrix} \quad (9)$$

$$\sum_{k=1}^{s+n} x_{khd} = \sum_{l=1}^{s+n} x_{kh(d+1)} \quad \begin{matrix} m > 2; \forall d \in \{1, \dots, m-2\}; \\ \forall h \in \{1, \dots, s\} \end{matrix} \quad (10)$$

$$\sum_{d=1}^m \sum_{k=1}^{s+n} x_{kld} = 1 \quad \forall l \in \{s+1, \dots, s+n\} \quad (11)$$

$$\sum_{k=1}^{s+n} x_{khd} = \sum_{l=1}^{s+n} x_{hld} \quad \begin{matrix} \forall d \in \{1, \dots, m\} \\ \forall l \in \{s+1, \dots, s+n\} \end{matrix} \quad (12)$$

$$\sum_{k=1}^{s+n} \sum_{l=1}^{s+n} x_{kld} (c_{kl} + T_l) \leq C \quad \forall d \in \{1, \dots, m\} \quad (13)$$

$$u_k - u_l + 1 \leq n(1 - \sum_{d=1}^m x_{kld}) \quad \forall k, l \in \{s+1, \dots, s+n\} \quad (14)$$

$$u_k \geq 0 \quad \forall k \in \{s+1, \dots, s+n\} \quad (15)$$

4.2. Tourism itinerary design model for hotels considering high-frequency changes

4.2.1. Model assumption

In the high-frequency itinerary design model for hotels, travelers will change accommodations several times during their trip to accommodate schedules in different regions, improving flexibility and diversity of experiences. This model is based on the following assumptions:

(i) Accommodation flexibility principle: travelers

are willing to change hotels to be closer to attractions or activity areas, improving the convenience and personalization of their trip.

- (ii) Luggage transfer assumption: in the high-frequency hotel change model, it is assumed that hotels provide free luggage delivery services between hotels. Since tourists do not need to transport their luggage themselves, the transfer process is not counted toward their daily sightseeing or commuting time.

4.2.2. Objective function

The objective function of the tourism itinerary design model for hotels with high-frequency changes is identical to that of the model for hotels with low-frequency changes, both aiming to minimize total travel time as shown in **Equation 4**.

4.2.3. Constraints

The tourism itinerary design model for high-frequency hotels has no constraints (**Equation 10**) than the model for low-frequency hotels. Its objective is to ensure that tourists return to a different hotel each day, thereby eliminating concerns related to luggage storage and reducing unnecessary travel distances to improve itinerary efficiency.

$$\sum_{k=1}^{s+n} x_{hkl} = \sum_{l=1}^{s+n} x_{lhl} \quad \forall h \in \{1, \dots, s\} \quad (16)$$

$$\sum_{k=1}^{s+n} x_{hkm} = \sum_{l=1}^{s+n} x_{lhm} \quad \forall h \in \{1, \dots, s\} \quad (17)$$

$$\sum_{l=1}^s \sum_{k=1}^{s+n} x_{kld} = 1 \quad \forall d \in \{1, \dots, m\} \quad (18)$$

$$\sum_{k=1}^s \sum_{l=1}^{s+n} x_{kld} = 1 \quad \forall d \in \{1, \dots, m\} \quad (19)$$

$$\sum_{k=1}^{s+n} x_{khd} = \sum_{l=1}^{s+n} x_{hl(d+1)} \quad \begin{matrix} m \geq 2; \forall d \in \{1, \dots, m-1\}; \\ \forall h \in \{1, \dots, s\} \end{matrix} \quad (20)$$

$$\sum_{d=1}^m \sum_{k=1}^{s+n} x_{kld} = 1 \quad \forall l \in \{s+1, \dots, s+n\} \quad (21)$$

$$\sum_{k=1}^{s+n} x_{khd} = \sum_{l=1}^{s+n} x_{hld} \quad \begin{matrix} \forall d \in \{1, \dots, m\} \\ \forall l \in \{s+1, \dots, s+n\} \end{matrix} \quad (22)$$

$$\sum_{k=1}^{s+n} \sum_{l=1}^{s+n} x_{kld} (c_{kl} + T_l) \leq C \quad \forall d \in \{1, \dots, m\} \quad (23)$$

$$u_k - u_l + 1 \leq n(1 - \sum_{d=1}^m x_{kld}) \quad \forall k, l \in \{s+1, \dots, s+n\} \quad (24)$$

$$u_k \geq 0 \quad \forall k \in \{s+1, \dots, s+n\} \quad (25)$$

5. Experimental testing

5.1. Data introduction

This study selected Chongqing as the case study city primarily for the following three reasons.

First, as a major tourist city in Southwest China and a representative “viral tourist city” in recent years, Chongqing possesses distinctive urban tourism characteristics and high research representativeness. According to data from the Chongqing Municipal Culture and Tourism Development Commission, the number of tourists visiting Chongqing is projected to exceed 500 million in 2025, representing an increase of approximately 5.7% over 2024, with total tourism revenue surpassing ¥550 billion.⁵¹ This indicates that Chongqing possesses a substantial tourist base and significant research value for the tourism market.

Second, Chongqing features a diverse array of attractions, including natural landscapes, historical and cultural sites, and urban nightscapes, among other tourism resources. This diversity effectively reflects differences in tourist preferences, providing a solid case foundation for research on the design of urban multiday personalized tourism itineraries.

Third, Chongqing’s attractions are geographically widespread, and tourists typically travel across multiple districts during their visits, making the city particularly suitable for research on the optimization of urban multiday personalized tourism itineraries.

5.1.1. Hotel data

Given that Chongqing has more than 15,000 hotels of various types, compiling a comprehensive list of their names and addresses is very difficult. To facilitate research analysis, we selected 15 five-star hotels representative of the region as candidate samples. Information on these hotels is

presented in **Table 7** (complete information on five-star hotels in Chongqing is shown in Table S1).

Table 7. Information on five-star hotels in Chongqing

ID	Name	Location
h_0	Aviva Hotel	106.507119,29.594805
h_1	Sheraton Hotel	106.586381,29.543289
h_2	Regent Hotel	106.570575,29.571163
...	...	...
h_{13}	R&F Le Méridien Hotel	106.570699,29.524017
h_{14}	Wellington Hotel	106.519865,29.610293

5.1.2. Attraction data

This study selected 41 popular tourist attractions in Chongqing as research subjects, and collected relevant data from the renowned Chinese travel platform Mafengwo (<https://www.mafengwo.cn/>). As shown in **Table 8**, the dataset included information on five dimensions: attraction ID, attraction name, geographic location, attraction score, and actual sightseeing duration reported by tourists (complete information on Chongqing attractions is provided in Table S2). Notably, the sightseeing duration data originates from genuine

user experience sharing on the platform, lending it significant value for reference.

As shown in **Figure 4**, this study conducted a visual analysis of the spatial distribution of hotels and tourist attractions in Chongqing. Red flags indicate attraction locations, while blue stars denote hotel locations, facilitating an intuitive comparison of their geographical distribution patterns.

5.1.3. Tourist preference data

To design personalized multiday urban travel itineraries, this study collected travel preference data from 15 tourists through questionnaires and oral interviews. Specific data points included: tour duration, travel duration, and preferred attractions (**Table 9**; the complete dataset is provided in Table S3). Data analysis indicates that most tourists schedule trips lasting three to five days, with daily activities concentrated between 8:00 AM and 11:00 PM. Accordingly, the model parameters in this study align with these preferences: a trip duration of three to five days and a daily travel duration of 15 h.

5.2. Experimental results

This study employed two models—one for designing tourism itineraries with low-frequency hotel changes and another for high-frequency hotel changes—solved using the branch-and-bound algorithm. The model and algorithm were compiled using the Gurobi 11.0.1 solver, and the entire experimental process was conducted in the PyCharm environment. The experimental results

Table 8. Chongqing attractions information

ID	Name	Location	Score	Sightseeing duration (mins)
a_{15}	Hongyadong	106.579297,29.56206	99	180
a_{16}	Erchang Cultural and Creative Park	106.539862,29.55103	98	90
a_{17}	Xiahaoli	106.592806,29.554972	97	120
a_{18}	Nanshan Scenic Area	106.604249,29.534642	96	240
a_{19}	Ciqikou Ancient Town	106.448944,29.580472	96	120
...	...	...	...	...
a_{54}	Red Rock Revolutionary Memorial Hall	106.499191,29.553953	73	90
a_{55}	Cai Jia Central Forest Park	106.492125,29.736049	72	180



Figure 4. Distribution map of Chongqing attractions and hotels

Table 9. Personal preference data of tourists

Tourist	Days	Total travel duration	Preferred attractions
1	3	9:00–22:00	$a_{15}, a_{16}, a_{25}, a_{38}, a_{43}, a_{37}, a_{35}$
2	3	12:00–01:00	$a_{15}, a_{16}, a_{25}, a_{38}, a_{43}, a_{37}, a_{35}, a_{39}$
3	3	8:00–23:00	$a_{26}, a_{28}, a_{19}, a_{34}, a_{36}, a_{15}, a_{22}, a_{37}, a_{35}$
4	3	10:00–21:00	$a_{26}, a_{28}, a_{19}, a_{34}, a_{36}, a_{32}, a_{22}, a_{46}$
5	3	8:00–23:00	$a_{19}, a_{18}, a_{39}, a_{42}, a_{16}, a_{31}, a_{30}, a_{23}, a_{22}$
6	4	13:00–02:00	$a_{43}, a_{15}, a_{16}, a_{20}, a_{35}, a_{34}, a_{33}, a_{23}, a_{18}$
...	...	...	...
26	5	9:00–23:00	$a_{15}, a_{16}, a_{17}, a_{25}, a_{28}, a_{34}, a_{35}, a_{36}, a_{38}, a_{40}, a_{41}, a_{45}, a_{48}, a_{50}$
27	5	10:00–23:00	$a_{15}, a_{20}, a_{25}, a_{28}, a_{30}, a_{31}, a_{35}, a_{36}, a_{38}, a_{39}, a_{43}, a_{46}, a_{49}, a_{50}, a_{54}$
28	5	8:00–21:00	$a_{28}, a_{19}, a_{20}, a_{21}, a_{23}, a_{25}, a_{28}, a_{32}, a_{33}, a_{36}, a_{38}, a_{40}$ $a_{41}, a_{43}, a_{48}, a_{50}, a_{55}$
29	5	9:00–20:00	$a_{16}, a_{19}, a_{20}, a_{22}, a_{27}, a_{29}, a_{30}, a_{33}, a_{36}, a_{38}, a_{40}, a_{44}$ $a_{45}, a_{47}, a_{48}, a_{50}, a_{51}$
30	5	7:00–20:00	$a_{15}, a_{16}, a_{17}, a_{18}, a_{19}, a_{20}, a_{23}, a_{24}, a_{26}, a_{30}, a_{32}, a_{33}$ $a_{37}, a_{45}, a_{48}, a_{51}, a_{53}$

considering tourist preferences are presented in **Table 10** (the complete dataset is provided in Table S4), including the optimal solution (C_{Best}),

the gap between the optimal solution and the current solution (Gap), and the solution time (T) under different hotel change models. Since the

proposed model is a minimization problem, Gap represents the relative difference between the best feasible objective value and the lower bound obtained during the branch-and-bound process. The calculation formula is shown in **Equation 26**, where C_{Best} denotes the best feasible objective value obtained by the solver, and C_{Bound} denotes the lower bound obtained during the branch-and-bound process. A Gap value of 0 indicates that the global optimal solution has been proven.

$$Gap = \frac{|C_{Best} - C_{Bound}|}{|C_{Best}|} \times 100\% \quad (26)$$

To further validate the comparative results between the two models, a paired sample t -test was conducted on the C_{Best} values obtained from the 30 tourist preference instances, and the statistical results are reported in **Table 11**.

The results of the paired t -test in **Table 11** show a t -value of 8.552 and a p -value of less than 0.001, indicating a significant difference in the C_{Best} values between the low-frequency hotel change model and the high-frequency hotel change model. Additionally, the mean C_{Best} value of the high-frequency hotel-change model was lower than that of the low-frequency hotel-change model, suggesting that the high-frequency model can effectively reduce the total travel time of the

tourism itinerary.

In addition, to provide a baseline comparison, **Table 12** presents the experimental results for the two hotel change models without considering individual tourist preferences. This setting differs from **Table 10**, which is based on 30 personalized tourist preference instances with different travel durations, time windows, and preferred attractions. In **Table 12**, the experiments used the same set of candidate attractions, did not impose individual preferred-attraction lists, and were conducted under fixed trip durations of 3, 4, and 5 days.

Without considering tourist preferences, the 3–5-day itinerary arrangements based on a low-frequency hotel-change model, along with sightseeing duration, commuting duration, and rest duration, are shown in **Table 13**.

Without considering tourist preferences, the itineraries arrangements for 3–5-day itineraries based on a high-frequency hotel-change model, along with sightseeing duration, commuting duration, and rest duration, are shown in **Table 14**.

Figures 5 and 6, respectively, illustrate the optimal itineraries and time allocations for 3–5 days of personalized urban tourism with differ-

Table 10. Experimental results considering tourist preferences

Tourist	Days	Low-frequency hotel changes			High-frequency hotel changes		
		C_{Best}	Gap (%)	Time (s)	C_{Best}	Gap (%)	Time (s)
1	3	761.6	0	1.04	760.51	0	0.75
2	3	822.73	0	1.61	822	0	1.38
3	3	1,009.78	0	1.20	1,008.1	0	0.38
4	3	866.69	0	1.35	861.41	0	0.36
5	3	1,388.49	0	2.08	1,385.37	0	0.32
6	4	1,271.41	0	2.16	1,268.7	0	3.47
...	...	...	...	...	...	...	...
26	5	1,381.86	0	83.42	1,363.26	0	4.36
27	5	1,456.53	0	122.45	1,446.16	0	4.45
28	5	1,759.77	0	3600	1,741.59	0	47.48
29	5	1,607.26	0	30.85	1,596.06	0	10.15
30	5	1,715.65	0	542.54	1,706.05	0	17.07

Table 11. Paired-sample t -test results of C_{Best} values

Variable	Low-frequency hotel changes	High-frequency hotel changes	t -value	p -value
C_{Best}	1,236.1920	1,227.4116	8.552	<0.001

Table 12. Experimental results without considering tourist preferences

Tour duration	Low-frequency hotel changes			High-frequency hotel changes		
	C_{Best}	Gap (%)	Time (s)	C_{Best}	Gap (%)	Time (s)
3	2,299.86	0	504.48	2,291.55	0	128.94
4	2,957.51	0.5896%	11,744.74	2,939.13	0.1427%	11,923.43
5	3,519.98	0.6814%	11,734.82	3,497.05	0.2777%	11,915.85

Table 13. Optimal itineraries for low-frequency hotel changes

Duration	Tourist itinerary	Sightseeing duration (min)	Commuting duration (min)	Rest duration (min)
$d = 3$	1: $[h_2, a_{23}, a_{20}, a_{24}, a_{28}, a_{19}, a_{25}, h_2]$	720	160	20
	2: $[h_2, a_{32}, a_{31}, a_{18}, a_{26}, a_{29}, a_{16}, a_{30}, h_2]$	720	160	20
	3: $[h_2, a_{27}, a_{21}, a_{22}, a_{17}, a_{15}, h_2]$	720	180	0
$d = 4$	1: $[h_8, a_{16}, a_{29}, a_{36}, a_{38}, a_{35}, a_{30}, a_{37}, h_8]$	690	150	60
	2: $[h_8, a_{26}, a_{18}, a_{17}, a_{31}, a_{15}, a_{32}, a_{33}, h_8]$	720	160	20
	3: $[h_8, a_{23}, a_{20}, a_{34}, a_{22}, a_{21}, a_{27}, h_8]$	690	210	0
	4: $[h_8, a_{25}, a_{19}, a_{39}, a_{28}, a_{40}, a_{24}, h_8]$	690	150	60
$d = 5$	1: $[h_8, a_{23}, a_{24}, a_{20}, a_{34}, a_{22}, a_{21}, h_8]$	660	230	10
	2: $[h_8, a_{46}, a_{29}, a_{36}, a_{38}, a_{41}, a_{42}, a_{35}, a_{49}, a_{16}, h_8]$	690	180	30
	3: $[h_8, a_{48}, a_{26}, a_{18}, a_{17}, a_{31}, a_{33}, h_8]$	600	130	170
	4: $[h_8, a_{45}, a_{43}, a_{39}, a_{28}, a_{40}, a_{19}, a_{44}, a_{25}, h_8]$	720	150	30
	5: $[h_8, a_{47}, a_{32}, a_{15}, a_{27}, a_{50}, a_{37}, a_{30}, h_8]$	660	130	110

Table 14. Optimal itineraries for high-frequency hotel changes

Duration	Tourist itinerary	Sightseeing duration (min)	Commuting duration (min)	Rest duration (min)
$d = 3$	1: $[h_{10}, a_{17}, a_{22}, a_{21}, a_{27}, a_{15}, h_{10}]$	720	180	0
	2: $[h_{10}, a_{32}, a_{31}, a_{18}, a_{26}, a_{29}, a_{16}, a_{30}, h_9]$	720	120	60
	3: $[h_9, a_{23}, a_{20}, a_{24}, a_{28}, a_{19}, a_{25}, h_9]$	720	150	30
$d = 4$	1: $[h_{10}, a_{31}, a_{17}, a_{18}, a_{26}, a_{33}, a_{32}, a_{15}, h_{10}]$	720	130	50
	2: $[h_{10}, a_{30}, a_{37}, a_{27}, a_{21}, a_{22}, a_{34}, h_{11}]$	720	180	0
	3: $[h_{11}, a_{20}, a_{23}, a_{24}, a_{40}, a_{28}, a_{39}, h_6]$	660	120	120
	4: $[h_6, a_{38}, a_{36}, a_{29}, a_{16}, a_{35}, a_{25}, a_{19}, h_6]$	690	110	100
$d = 5$	1: $[h_{10}, a_{32}, a_{33}, a_{48}, a_{26}, a_{18}, a_{17}, a_{31}, h_{10}]$	630	110	160
	2: $[h_{10}, a_{15}, a_{37}, a_{16}, a_{49}, a_{35}, a_{45}, a_{44}, a_{25}, h_1]$	720	110	70
	3: $[h_1, a_{23}, a_{24}, a_{20}, a_{34}, a_{22}, a_{21}, h_{12}]$	660	200	40
	4: $[h_{12}, a_{27}, a_{50}, a_{30}, a_{47}, a_{46}, a_{29}, a_{36}, a_{38}, a_{41}, h_6]$	720	110	70
	5: $[h_6, a_{28}, a_{40}, a_{39}, a_{43}, a_{19}, a_{42}, h_6]$	600	100	200

ent hotel change frequencies. **Figure 7** specifically shows the commuting time comparisons for the optimal tourism itineraries.

5.3. Comparative analysis

5.3.1. Economic analysis of optimal tourism itineraries with different hotel change frequencies

Using the quantification formulas for C_{11} , C_{12} , C_{13} , total ticket costs (C_{11}), total hotel costs (C_{12}), and total commuting costs (C_{13}) for 3–5-day itineraries of the two models can be calculated respectively, as shown in **Table 15**.

In the economic analysis of tourism itinerary planning, the focus was on comparing three dimensions: total ticket, hotel, and commuting costs. Since both models visited the same attractions, the ticket costs were identical, averaging ¥295 each. However, in terms of total hotel costs, the high-frequency change model consistently incurred higher expenses than the low-frequency change model due to additional hotel selections and luggage transfer services. The average costs were ¥2,120 and ¥2,037, respectively, a difference of ¥83. Notably, the high-frequency change model effectively reduces transportation costs between attractions and hotels by optimizing daily hotel locations.

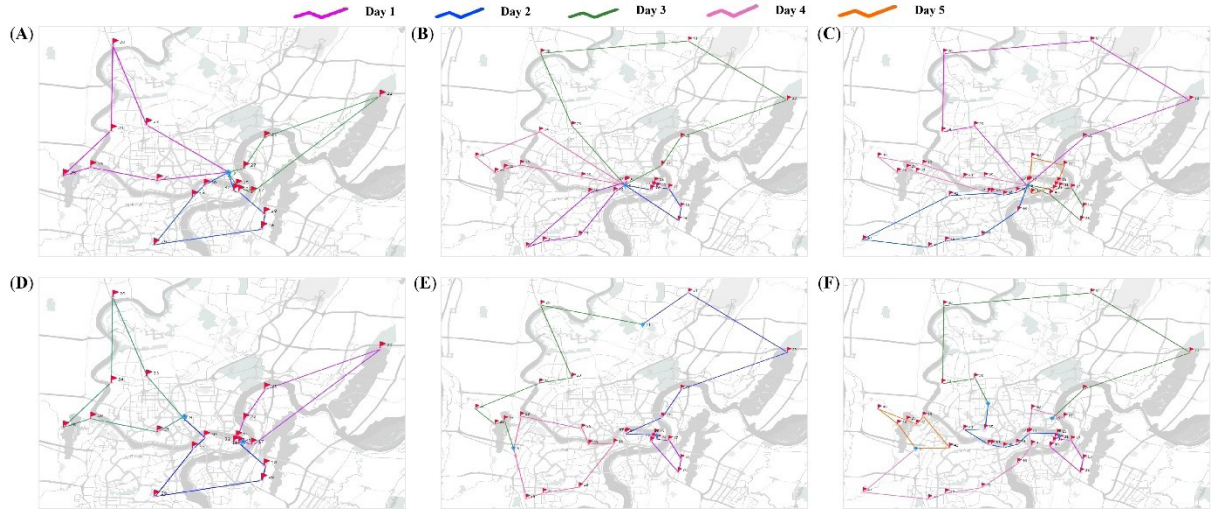


Figure 5. Optimal tourism itinerary design for different modes in Chongqing ($d = 3-5$). Tourism route map for low-frequency hotel changes: (A) $d = 3$; (B) $d = 4$; (C) $d = 5$. Tourism route map for high-frequency hotel changes: (D) $d = 3$; (E) $d = 4$; (F) $d = 5$.

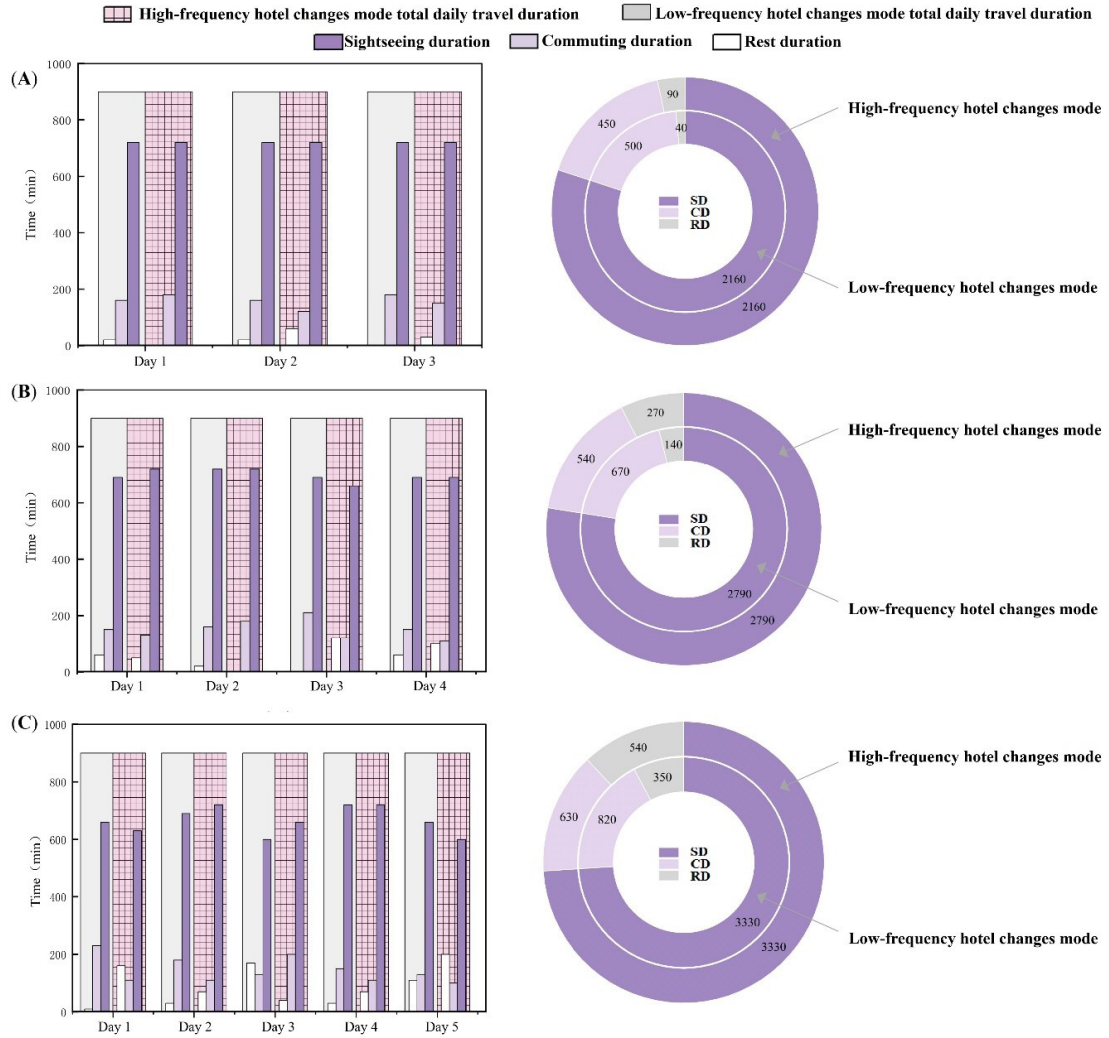


Figure 6. Time comparison analysis of optimal tour itineraries. (A) $d = 3$; (B) $d = 4$; (C) $d = 5$.

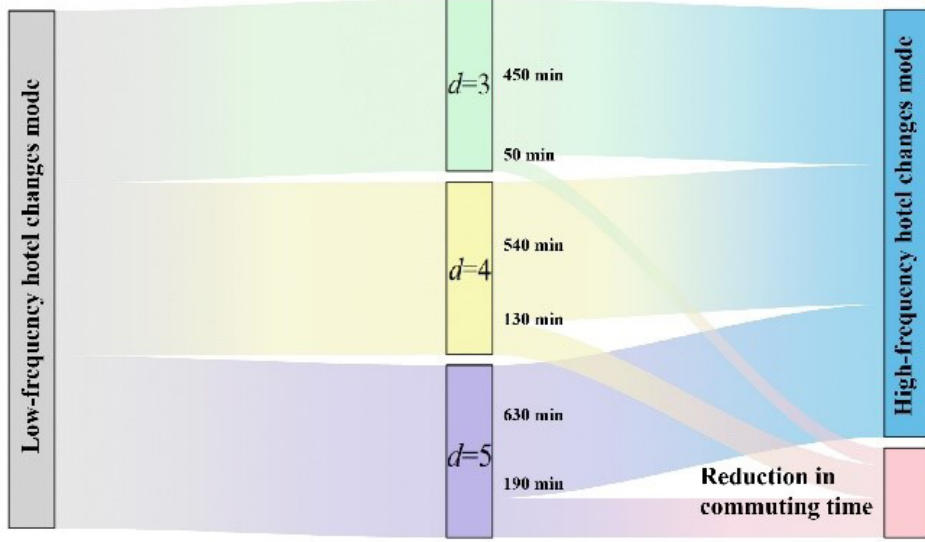


Figure 7. Commuting time comparison for optimal tourism itineraries ($d = 3-5$).

Table 15. Economic indicator values with different tourism itinerary plans

Tour duration	Low-frequency hotel changes			High-frequency hotel changes		
	C_{11}	C_{12}	C_{13}	C_{11}	C_{12}	C_{13}
$d = 3$	130	1,600	484	130	1,680	440
$d = 4$	368	2,030	680	368	2,130	572
$d = 5$	388	2,480	728	388	2,550	596
Mean	295	2,037	631	295	2,120	536

For the 3–5-day itineraries, the cost savings amounted to ¥44, ¥108, and ¥132, respectively. On average, the high-frequency change model's total commuting cost was ¥ 536, significantly lower than the low-frequency change model's ¥631—a reduction of ¥95. This demonstrates its substantial efficiency in minimizing cross-regional commuting.

Overall, while the high-frequency change model increases hotel costs, it significantly reduces commuting expenses. As the number of travel days increases, the savings on commuting costs become increasingly pronounced, demonstrating strong potential for cost optimization.

Convenience analysis of optimal tourism itineraries with different hotel change frequencies

Using the quantification formulas for C_{21} , C_{22} , C_{23} , total travel distance (C_{21}), distance from hotel to attractions (C_{22}), and distance

from attractions back to hotel (C_{23}) for 3–5-day itineraries of the two models can be calculated respectively, as shown in Table 16.

In the convenience analysis of tourism itinerary planning, the comparison focused on three dimensions: total travel distance, the distance from the hotel to attractions, and the distance from attractions back to the hotel. Regarding total travel distance, the high-frequency hotel-change model effectively reduces the commuting burden. For 3–5-day itineraries, total distances decreased by 22 km, 54 km, and 66 km, respectively. On average, the high-frequency model recorded a total travel distance of 268 km, significantly lower than the low-frequency model's 315 km, representing a reduction of 47 km. Regarding the distance from the hotel to attractions, the high-frequency hotel-change model also demonstrated better performance. For the 3-day itineraries, the distance decreased

Table 16. Convenience indicator values with different tourism itinerary plans

Tour duration	Low-frequency hotel changes			High-frequency hotel changes		
	C_{21} (km)	C_{22} (km)	C_{23} (km)	C_{21} (km)	C_{22} (km)	C_{23} (km)
$d = 3$	242	4.07	3.2	220	2.44	2.09
$d = 4$	340	5.19	4.47	286	4.74	3.42
$d = 5$	364	3.81	3.29	298	1.80	3.65
Mean	315	4.36	3.65	268	2.99	3.05

from 4.07 km to 2.44 km, corresponding to a reduction of approximately 40.0%. For the 5-day itineraries, the distance decreased from 3.81 km to 1.80 km, corresponding to a reduction of approximately 52.8%. Across all cases, the average distance from the hotel to attractions decreased from 4.36 km in the low-frequency model to 2.99 km in the high-frequency model, representing a 31.4% reduction. For the distance from attractions back to hotels, the high-frequency hotel change model maintained its lead in 3-day and 4-day itineraries. Although it was slightly higher than the low-frequency model in 5-day itineraries, the high-frequency model's average distance of 3.05 km remained superior to the low-frequency model's 3.65 km, representing a 16.4% reduction. This demonstrates excellent overall convenience.

Overall, the high-frequency hotel change model minimizes distances between attractions and accommodations, reducing unnecessary travel time and delivering a more convenient and efficient travel experience.

5.3.3. Experience analysis of optimal tourism itineraries with different hotel change frequencies

Using the quantification formulas for C_{31} , C_{32} , C_{33} , total attraction score (C_{31}), total hotel score (C_{32}), and total rest duration (C_{33}) for 3-day, 4-day, and 5-day itineraries of the two models can be calculated respectively, as shown in **Table 17**.

In the experiential analysis of tourism itinerary planning, the comparison focused on three dimensions: total attraction scores, total hotel scores, and total rest duration. Since the attractions visited were identical, the total attraction scores showed no difference between the two modes, with both averaging 87 points. Regarding hotel overall ratings, the high-frequency hotel change model demonstrated a consistent advantage. Although it scored slightly lower than the low-frequency model on the 3-day itinerary, it outperformed it on both the 4-day and 5-day itineraries, highlighting its flexibility in hotel selection for multiday trips. The most significant

Table 17. Experience indicator values with different tourism itinerary plans

Tour duration	Low-frequency hotel changes			High-frequency hotel changes		
	C_{31}	C_{32}	C_{33} (min)	C_{31}	C_{32}	C_{33} (min)
$d = 3$	90	97	40	90	96	90
$d = 4$	87	95	140	87	96	270
$d = 5$	85	95	350	85	95	540
Mean	87	96	177	87	96	300

advantage lies in total rest duration. The high-frequency hotel-changing model maintained its leadership across all itinerary lengths: 50 minutes longer for the 3-day itinerary, 130 minutes longer for the 4-day itinerary, and 190 minutes longer for the 5-day itinerary. On average, the high-frequency model achieved 300 minutes of total rest duration, significantly higher than the low-frequency model's 177 minutes, representing a difference of 123 minutes.

Overall, the high-frequency hotel change model enhances the quality of hotel experiences while maintaining attraction standards, increasing total rest time and enabling visitors to gain richer travel experiences.

5.4. Discussion

As shown by the experimental results in Section 5.2, the high-frequency hotel change mode achieved lower C_{Best} values in every case, indicating that it performs better in minimizing total travel time. This is because the high-frequency hotel-change mode adjusts the hotel location based on the tourist's primary daily sightseeing area, bringing the hotel closer to that day's attractions and thereby reducing unnecessary commuting between areas. This is particularly evident in the 4-day and 5-day itineraries, where tourists cover a wider area. The low-frequency change mode tends to result in repetitive commuting, with tourists departing from and returning to the same hotel every day, whereas the high-frequency change mode reduces this inefficient travel distance by changing hotels, leading to a more optimal target value for the tourism itinerary.

A further comparison of satisfaction levels in section 5.3 reveals that the low-frequency hotel change model offers certain advantages in economy, primarily by reducing the additional costs associated with changing hotels and transferring luggage. However, in the convenience and experience dimensions, the high-frequency hotel change model demonstrates a more pronounced advantage: on the one hand, this model shortens commuting distances between hotels and attractions, as well as between attractions themselves, thereby improving itinerary fluidity and transportation connectivity; on the other hand, the reduction in commuting time allows tourists to gain more sightseeing duration and rest duration, thereby enhancing the overall travel experience. Although the high-frequency change model entails additional costs, the improvements in convenience and experience offset them, ultimately resulting in higher overall

satisfaction.

The above results indicate that, in the context of an urban multiday personalized tourism itinerary, hotel arrangements are not merely a secondary consideration in itinerary design but also influence tourists' evaluation of the overall journey. Most existing studies on tourism itinerary design treat hotels as fixed conditions, whereas our study incorporates the frequency of hotel changes as a dynamic decision-making factor in the model and quantitatively analyses tourist satisfaction across three dimensions: economy, convenience, and experience. The results indicate that a high-frequency hotel-change model can effectively improve the quality of tourism itineraries and enhance tourist satisfaction, thereby offering new research insights into the coordinated optimization of urban multiday personalized tourism itineraries and accommodations.

5.5. Policy implications

Based on the optimization results for urban multiday personalized tourism itineraries under different hotel change frequencies, this study further analyzes the implications of these findings for urban tourism management and the development of smart tourism.

First, to promote the development of urban multiday personalized tourism, tourism management departments should place greater emphasis on coordinating hotel accommodation resources with the spatial distribution of attractions. By optimizing hotel distribution, improving transportation connections to attractions, and enhancing accessibility across different areas, it is possible to effectively reduce long-distance commuting for tourists, thereby enhancing the overall tourist experience and the city's tourism attractiveness. At the same time, for cities with an uneven distribution of popular and less-frequented attractions, measures such as guiding accommodation resources and optimizing transportation can promote rational tourist flow between different areas, thereby alleviating tourism pressure on core attractions.

Second, as the development of smart tourism in cities continues to advance, relevant departments can further promote the establishment of an integrated tourism service system linking "attractions, transportation, and hotels," incorporating the high-frequency hotel change model into personalized tourism service platforms. Particularly in multiday, multi-area

urban tourism scenarios, hotels should not be treated merely as fixed supporting facilities. Instead, accommodation arrangements, attraction selection, and transportation organization should be considered in a coordinated manner. By integrating the high-frequency hotel change model, spatial connections between accommodations and attractions can be optimized, thereby reducing cross-area commuting time and improving the efficiency of itinerary planning as well as tourist satisfaction.

Finally, the results of this study also indicate that the model of high-frequency hotel changes can effectively enhance satisfaction with urban multiday personalized tourism itineraries; however, its implementation effectiveness is closely linked to the quality of luggage transfer services. Therefore, in the future development of urban tourism service systems, efforts should be made to further improve luggage transfer and temporary storage services between hotels. This would alleviate the burden of luggage handling associated with frequent hotel changes, thereby providing better support for the “travel light” model and further enhancing the overall travel experience for tourists.

6. Conclusion

Against the backdrop of digital technologies reshaping the cultural and tourism industry, personalized urban tourism has emerged as an industry trend by precisely addressing diverse visitor needs.⁵² However, the issue of hotel change frequency during multiday itineraries has long been overlooked. This study incorporates hotel change frequency as a key factor into personalized urban tourism itinerary design, establishing a Satisfaction Evaluation model based on economy, convenience, and experience dimensions. It further proposes itinerary design models for different hotel change frequencies, solved using an efficient branch-and-bound algorithm.

In the Chongqing case study, a comparative analysis shows that frequent hotel changes are more effective at enhancing itinerary satisfaction. Economically, while the high-frequency model increases total hotel costs, it significantly reduces commuting costs. In terms of convenience, it reduces total travel distance by 47 km compared to the low-frequency model. Regarding the experience dimension, the high-frequency model increases rest time by reducing commuting duration by 123 minutes, allowing deeper immersion in attraction visits.

Through theoretical innovation and computational experiments, this study establishes the critical importance of frequent hotel changes in multiday personalized urban tourism itineraries. As technology evolves and ecosystems mature, “light-packing travel” enabled by luggage transfer services will become a core driver for enhancing urban tourism competitiveness, propelling the cultural and tourism industry toward greater efficiency, customization, and sustainability. Future research should incorporate additional uncertainties—such as weather fluctuations, attraction time windows, spontaneous points of interest, or emergency situations—to continuously elevate tourist satisfaction.

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Conflict of interest

The authors declare no conflicts of interest.

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Availability of data

The data that support the findings of this study are openly available in Mendeley Data at <https://data.mendeley.com/datasets/mm9cdtj8v3/1>, reference number: mm9cdtj8v3.

AI tools statement

All authors confirm that no AI tools were used in the preparation of this manuscript.

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