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RESEARCH ARTICLE

A Group Travel Recommender System Based on Group Approximate Constraint Satisfaction

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ABSTRACT In today's travel landscape, there's a growing demand for experiences that cater specifically to group travelers, whose needs often differ from those of solo travelers. Despite the abundance of information available on community sites like TripAdvisor, the extensive planning required can be time-consuming. This highlights the need for a recommendation system tailored to the nuances of group travel. Our study focuses on enhancing travel experiences for groups by proposing customized travel packages that take into account various preferences, such as destinations, budget constraints, and individual components like flights, hotels, and events. We introduce a method that combines Collaborative Filtering (CF) for destination recommendations with a group consensus decision-making process, factoring in individual preferences as constraints. This approach led to the creation of the GRec_Tr system, which not only suggests travel destinations but also offers comprehensive package recommendations, including flights, hotels, and activities. Our method aims to improve the overall travel experience, increase traveler satisfaction, and potentially boost sales for travel agencies. It also expands the scope of traditional CF-based systems by integrating diverse travel components into the recommendation process.

INDEX TERMS Approximate constraint satisfaction, collaborative filtering, group travel recommendation, group satisfaction, travel package.

I. INTRODUCTION

In the smart travel ecosystem, community sites like TripAdvisor (www.tripadvisor.com) are pivotal in shaping travelers' decisions and plans. These platforms enable users to share and access a wealth of travel information and tips [1], [2], [3], which in turn influences their travel itineraries [4], [5], [6], [7]. Despite the richness of information on these sites, the volume of content often results in travelers spending considerable time and effort in planning. Challenges such as selecting suitable airlines, hotels, and amenities that fit their preferences and budget further complicate the process. To mitigate these issues and enhance customer service, leading global travel companies like Travelocity.com have developed travel recommender systems. These systems, by analyzing a traveler's previous trips, offer personalized travel planning services [8]. Notable examples include the TripMatcher by Triplehop and the expert advice platform by Vacation Coach [9], [10].

Group travelers encounter specific challenges when utilizing these travel recommendation systems. With the rise of information and communication technologies, group interactions predominantly occur in virtual spaces, altering the dynamics of resolving conflicts that stem from differing individual preferences during travel planning. This shift from traditional offline interactions demands a more nuanced approach. Moreover, most existing group recommendation systems aim to cater to the majority within a group by integrating individual preferences into a collective decision. This often leads to the marginalization of minority opinions, causing dissatisfaction among some group members [11]. Additionally, traditional systems typically focus

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on recommending individual travel products or elements, making it difficult to address the complexities involved in planning group travel, where multiple components must be considered simultaneously.

The application of Collaborative Filtering (CF), despite being one of the most successful recommendation techniques, faces limitations in the context of group travel planning [12], [13], [14], [15], [16], [17], [18]. CF functions by recommending items based on user profiles and purchase histories, identifying 'neighbors' (users with similar preferences) to weigh their item evaluations more heavily. This method aims to predict items a user is likely to purchase. However, CF-based systems are generally designed for single products, which poses a challenge in recommending multiple, interrelated travel components like destinations, hotels, and flights. Furthermore, these systems are typically oriented towards individualized travel packages, not addressing the collective needs of groups planning to travel together. Therefore, there is an evident gap in the development of group travel recommendation systems capable of suggesting comprehensive travel packages that include a range of interconnected products tailored for groups.

In this study, we introduce the GRec_Tr, a novel group travel recommendation system specifically tailored for recommending travel packages that consist of multiple components to group travelers. The primary aim of GRec_Tr is not only to enhance the accuracy of recommendations but also to boost the overall satisfaction of each group member. The system distinguishes itself in two key aspects: First, it adapts the traditional CF-based approach to suit composite products such as travel destinations, flights, hotels, and attractions, acknowledging that group travel packages are inherently multifaceted. Additionally, since it is based on the CF method, it provides recommendations based on visit records and constraints rather than sensitive personal information such as age or gender, making it excellent privacy protection. Second, the complexity of assembling a group travel package, which must consider various constraints like the travel duration and budget preferences of each group member, is addressed innovatively. We have modeled the individual preferences of travelers as constraints and developed an approximate constraint satisfaction method that seeks to optimize the fulfillment of these individual preferences within the group's context.

Our proposed method executes its recommendation process in three distinct phases to meet its objectives. The initial phase focuses on analyzing the destination preferences of group travelers. By identifying groups with similar behaviors to the target group, the system determines their preferred destinations and subsequently generates a list of top N candidate destinations for the target group. The second phase involves modeling each traveler's individual preferences (such as flight types, accommodation styles, and price ranges) as approximate constraints, which are then integrated into a comprehensive set of group-level approximate constraints. The final phase compares the travel package components of the candidate destinations against both group and individual approximate constraints. As a result, the system generates M optimal travel packages that satisfy the group's constraints while minimizing individual compromises. These packages are then proposed to the group travelers. To validate the effectiveness of GRec_Tr, benchmark systems were established, and experiments were conducted. Participant attitudes were gauged using a Likert 5-point scale, assessing factors like relevance, novelty, unexpectedness, serendipity, usefulness, and overall satisfaction with GRec_Tr's recommendations [8], [14], [19], [20]. The results demonstrated that our proposed group travel recommendation system effectively aids travelers in selecting appropriate destinations, flights, hotels, and activities.

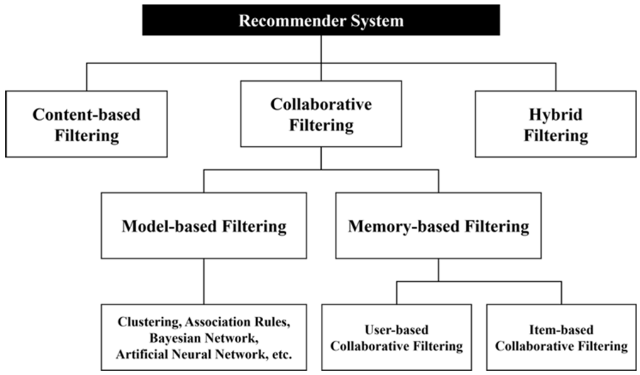

FIGURE 1. Classification of the recommender system [24].

II. RESEARCH BACKGROUND

A. TRAVEL RECOMMENDER SYSTEMS

Recommender systems are designed to present items that are most likely to be preferred by a target user, thereby mitigating the issue of information overload [21], [22], [23]. As depicted in FIGURE 1, these systems are generally categorized into three types: Content-based Filtering (CB), Collaborative Filtering (CF), and Hybrid Filtering [24].

CB recommends items by matching attributes similar to those of previously purchased items by the user. However, its effectiveness is largely dependent on the precision of feature engineering related to item attributes; irrelevant attributes can lead to unsuitable recommendations. On the other hand, CF recommends items based on the preferences of 'neighbors' – users with similar tastes. It can be further divided into model-based and memory-based filtering. However, CF relies heavily on users' past purchase history, leading to the 'cold start' problem, where it struggles to make recommendations for new users or items. Additionally, CF encounters scalability issues, with recommendation quality diminishing as the number of users or items increases. Lastly, Hybrid Filtering seeks to amalgamate CB and CF techniques in various ways, aiming to overcome the limitations of each and enhance the overall quality of recommendations.

Firstly, CB recommends items based on attributes similar to those of items previously purchased by the target user. However, CB has limitations, as feature engineering related to item attributes is critical; using attributes unrelated to the recommendation can lead to inappropriate suggestions [25]. Next, CF recommends items based on the preferences of neighbors with similar preferences to the target user. it can be further categorized into model-based and memory-based filtering. However, it relies on the user's past purchase history, leading to the cold start problem, where it becomes challenging to recommend for new users or new items [26], [27], [28]. Moreover, it faces a scalability issue where the quality of recommendations decreases as the number of items or users increases [15], [29]. Lastly, Hybrid Filtering combines both CB and CF techniques in various ways to address the shortcomings of each and provide better recommendations.

Travel recommender systems have been developed to analyze tourists' past travel histories, offering personalized planning services [8]. There's a wide spectrum of research in this field, focusing on recommending destinations, travel routes, hotels, flights, restaurants, and travel packages, among others. Notable contributions include Linden et al. [30] who presented a model for recommending flight schedules based on progressively inferred user preferences. Liu et al. [31] developed the TAST (Tourist-Area-Season Topic) model, generating personalized travel package recommendations through topic model representations. Majid et al. [32] focused on context-aware destination recommendations using travel preferences from social media. Kotiloglu et al. [33] introduced a personalized travel recommendation framework utilizing CF and Iterated Tabu Search algorithms. Hossain et al. [34] proposed a system for personalized travel destination recommendations using a combination of POI(Point of Interest) filtering, BFS (Breadth First Search) algorithm for exploring POIs, and Dijkstra algorithm for optimal route planning. Chen et al. [35] introduced the TRKG (Travel Recommendation with Keywords Generation) model for simultaneous travel recommendations and keyword generation. Zhou et al. [36] proposed CTLTR (Contrastive Trajectory Learning for Tour Recommendation), enhancing data sparsity through self-supervised learning and leveraging unique POI dependencies. Zhuang and Kim [37] developed a BERT-based hotel recommendation system predicting evaluation criteria and overall satisfaction from TripAdvisor reviews. Finally, Lee et al. [38] combined CF and content-based filtering to develop a restaurant recommendation system.

Despite this ongoing research focusing on individual traveler recommendations, there remains a notable gap in addressing the needs of group travelers. This gap underlines the necessity for systems that cater to the distinct requirements of group travel planning [39].

B. GROUP RECOMMENDER SYSTEMS

Group recommender systems function by classifying users into distinct segments and providing recommendations tailored to these specific groups [20], [40]. The operational methodology of these systems generally falls into two categories. The first approach involves the aggregation of individual member profiles to form a collective group profile, which is then used to recommend items that align with this combined profile [40]. The second approach focuses on generating personalized recommendations for each group member individually, and then amalgamating these individual recommendations to formulate a singular group recommendation [41]. Chen et al. [42] introduced a group recommender system within the Collaborative Filtering (CF) framework, employing genetic algorithms to predict group member interactions and estimate potential item ratings. Kim et al. [40] developed a system specifically for online communities, designed in two phases for efficient group recommendations and increased individual member satisfaction. The first phase used conventional CF to generate group profile-based recommendations, while the second phase employed relevance-based filtering for refinement. Further, Kim et al. [20] proposed Commenders (Community Recommender Procedures), a two-step process starting with CF-based recommendations using community book preferences and functional information, followed by filtering using individual member keyword preferences. Christensen et al. [43] combined CF, Content-Based (CB) filtering, and demographic information filtering to provide personalized recommendations for both individuals and groups. Qin et al. [44] presented a technique for recommending to large groups, which first segmented them into subgroups, applied CF to each, and then integrated these recommendations. Cao et al. [45] introduced a system utilizing an attention network to form group representations and applied Neural Collaborative Filtering (NCF) for user-item interactions. Huang et al. [46] proposed a Multi-attention based group recommendation model focusing on closely-related group features and group preferences towards items. Lastly, Huang et al. [47] developed a two-step deep learning model for group recommendations, encompassing Group Representation Learning (GRL) and Group Preference Learning (GPL).

However, a significant limitation of most existing group recommender systems is their focus on single products. Group travel products, in contrast, are often composite packages encompassing various components such as travel destinations, flights, hotels, and activities. This multifaceted nature poses challenges when applying traditional recommendation methods, particularly because group travel must account for the individual preferences and constraints of each member regarding flights, hotels, and activities. As a result, there is a need for innovative methods specifically tailored to address these complex requirements of group travel.

C. APPROXIMATE CONSTRAINT SATISFACTION PROBLEM

The Constraint Satisfaction Problem (CSP) involves finding solutions that satisfy a set of constraints within a specific scenario and a finite domain [48]. The main challenge is to assign values to variables in a way that all given constraints are met, considering the variables and their respective domains. Notable solutions to CSP include methods like constraint propagation [49], n-consistency checking [50], and backtracking [51]. However, a critical limitation of CSP is its assumption that a solution exists which satisfies all constraints, a process that can be prohibitively time-consuming in its worst-case scenarios [52].

To overcome these limitations, the Approximate Constraint Satisfaction Problem (ACSP) approach was developed. ACSP expands the scope by considering not only whether constraints are met, but also the degree of their satisfaction when assigning values to variables [8], [53]. The key to ACSP is differentiating between assignments based on how significantly they satisfy the constraints. In cases where two assignments do not markedly differ in satisfying a particular constraint, they are further compared using another constraint. For instance, consider a customer choosing between three hotels: A ($100, 3-star), B ($100, 4-star), and C ($200, 5-star). If the primary criterion is price, then hotels A and B, both being $100, are preferable over the more expensive hotel C. However, given that A and B are equally priced, the decision can then be refined using a secondary criterion, such as hotel grade. If the customer prefers a 4-star hotel, Hotel B would be chosen over Hotel A, illustrating how ACSP aids in decision-making by prioritizing and balancing multiple constraints.

III. GROUP TRAVEL PACKAGE RECOMMENDATION METHOD

A. INTRODUCTION

In the process of travel planning, travelers often consult with family, friends, and socially connected individuals, as well as scour travel community sites like TripAdvisor, to gather a wide range of travel information [54], [55]. However, sifting through such an extensive array of information to identify a travel package that aligns with personal preferences is not only time-consuming but also challenging. This difficulty is compounded by the task of distinguishing valuable information from the commercial biases prevalent on many travel sites. This process becomes even more complex in group recommendation systems, where it is essential to consider the preferences of each individual member [56]. The task of integrating these individual preferences to form a collective group preference, or merging recommendation lists for each member to create a group recommendation, often leads to dissatisfaction among some members of the group.

To address these challenges, our study introduces a novel group recommendation method based on Collaborative Filtering (CF). This method incorporates the automation of Word of Mouth, facilitating the construction of travel packages without the need for extensive information exploration. Additionally, we propose a travel package recommendation system specifically designed for group travelers. This

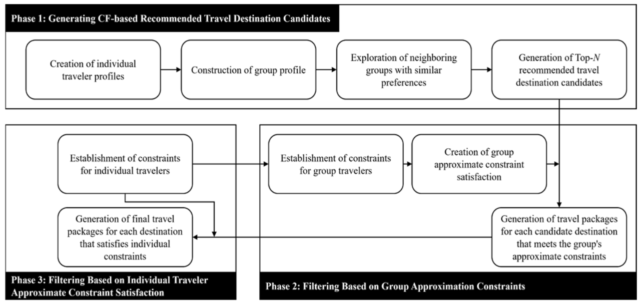

FIGURE 2. Overall procedure of GRec_Tr.

system employs the approximate constraint method, placing paramount importance on the individual preferences of group members. The primary goal of this research is to develop a system, named GRec_Tr, that not only models individual travelers' requirements as constraints but also automates the group decision-making process. This approach aims to significantly enhance the convenience and satisfaction of group travelers. The GRec_Tr system is structured in three stages, as depicted in FIGURE 2, strategically designed to meet these objectives.

In the initial phase of our proposed method, the GRec_Tr system analyzes the group's preferences for various destinations to identify neighboring groups with similar tastes. Based on this analysis, it recommends a list of Top-N travel destinations that are most likely to appeal to the target group. The second phase involves generating potential travel package candidates. This is achieved by comparing the components of the recommended destinations with the group travelers' approximate constraints, which include factors such as flight options, types of accommodations, and price ranges. In the final phase, the system aims to minimize the potential dissatisfaction of less assertive individual travelers by filtering out candidate packages that fail to meet specific individual constraints. This selective process results in the creation of the final list of Top-M recommended travel packages, ensuring that the recommendations are well-aligned with the preferences and constraints of all group members. By utilizing a two-step post-filtering process based on constraints for the initially recommended Top-N travel destinations, we expect to achieve operational efficiency in the recommendation system.

B. PHASE 1: GENERATING CF-BASED RECOMMENDED TRAVEL DESTINATION CANDIDATES

The initial stage in generating CF-based recommended travel destinations revolves around creating profiles for individual travelers, which subsequently underpin the formulation of group profiles. Within the ambit of travel recommendation systems, a traveler's profile, which is fundamental to CF-based recommendations, indicates their preferences for specific destinations. The GRec_Tr proposed in this research consolidates individual traveler profiles based on the study by Kim et al. [40] to produce profiles for groups of travelers. The profile for individual traveler i with regard to destination

j is depicted as a matrix R in the format $m \times n$, in accordance with equation (1).

$$R = \left\{ r_{i,j} \right\}, \quad i = 1 \; to \; m, \; j = 1 ton \tag{1}$$

In this equation, $r_{i,j}$ represents the rating given by traveler i for destination j, with the rating scale ranging from 1 to 5.

Consequently, the profile for group travelers g in relation to destination j is depicted as a matrix G in the format $c \times n$, aligned with equation (2).

$$G = \left\{ r^{AVG}_{g_{i,j}} \right\}, \quad g = 1 \; to \; c, \; j = 1 ton \tag{2}$$

Here, $r^{AVG}_{g_{i,j}}$ signifies the average rating of destination j given by individual traveler i belonging to group g.

The second stage involves identifying groups (referred to as "neighbor groups") that have similar preferences to the target group regarding destinations. In GRec_Tr, similarity is determined using the Pearson correlation coefficient. The similarity between group a and group b is computed as per equation (3).

$$sim\,(a, b) = corr_{ab} = \frac{\sum_j^n (r^{AVG}_{a_j} - \overline{r^{AVG}_a})(r^{AVG}_{b_j} - \overline{r^{AVG}_b})}{\sqrt{\sum_j^n (r^{AVG}_{a_j} - \overline{r^{AVG}_a})^2 - \sum_j^n (r^{AVG}_{b_j} - \overline{r^{AVG}_b})^2}} \tag{3}$$

In this equation, n represents the total number of destinations. $r^{AVG}_{a_j}$ and $r^{AVG}_{b_j}$ indicate the ratings for destination j by group a and group b, respectively. Additionally, $\overline{r^{AVG}_a}$ and $\overline{r^{AVG}_b}$ signify the average ratings across all destinations for groups a and b.

The final stage focuses on constructing a candidate list of N destinations that the target group is most likely to visit, utilizing the Travel Likelihood Score (TLS). The TLS for destination j concerning target group a is computed as indicated in equation (4).

$$TLS\,(a, j) = \frac{\sum_{g \in N_a} r^{AVG}_{g_{i,j}} \cdot sim(a, g)}{\sum_{g \in N_a} sim(a, g)} \tag{4}$$

Here, *sim(a,g)* represents the similarity between the target group a and the neighboring group g. The higher the TLS value, the more likely the target traveler group is to choose the destination. As a result, the top N destinations with the highest TLS values are selected as candidate destinations.

C. PHASE 2: FILTERING BASED ON GROUP APPROXIMATION CONSTRAINTS

Traditional CF-based recommendation systems generate a list of recommended destinations by comparing the destinations favored by the target user with those favored by the target user's neighbors. However, even if travelers visit the same destination, they can have different experiences. Moreover, travel packages for group travelers cannot satisfy the preferences of all individual travelers in the group. Yet, it's important to meet the needs of as many people in the group as possible without completely ignoring the needs of specific individual travelers. In this study, we assume the following: individual users in a group input constraints (e.g., mode of transport, type of accommodation) directly related to travel products or services. However, such constraints are not necessarily absolute. For example, an individual traveler might find a \$80 price difference in round-trip airfare difficult to accept, but a difference of about \$40 might be considered acceptable. Each individual user's constraints are independent, and each user can have multiple constraints with relative importance between them. It's assumed that conflicts between constraints are not allowed. These are general assumptions, and under these assumptions, GRec_Tr derives group travel constraints from individual traveler constraints. That is, GRec_Tr finds the intersection of individual traveler constraints to create a set of group constraints that represent general characteristics of the group.

Group travel constraints c for traveler group g are assumed to consist of p constraints, expressed as $\{c_{g,1}, c_{g,2}, \ldots, c_{g,p-1}, c_{\,i,p}\}$. If the constraint is continuous, the constraint of group g is defined as the intersection of the constraints of individual travelers belonging to group g. For instance, if customers A, B, and C are in the same group and have respective flight price constraints of "price $\leq$ 600", "price $\leq$ 650", and "price $\leq$ 500", the group's flight price constraint becomes "price $\leq$ 500". If the constraint is categorical, the constraint of group g is defined by majority rule among individual traveler constraints within group g. For example, if customers A, B, and C are in the same group with flight selection constraints of "flight = Korean Air", "flight = JAL", and "flight = Korean Air", the group's flight constraint becomes "flight = Korean Air".

Therefore, if we define group constraint as $c_{g,k}$, the component of the travel package that meets the constraint as θ_k, and the error of group constraint satisfaction as $e(c_{g,k}, \theta_k)$, firstly, when the group constraint is continuous data, the error of group constraint satisfaction is defined as shown in equation (5).

$$\begin{aligned} &e\left(c_{g,k} = d_1, \theta_k\right) \\ &\qquad = |\theta_k - d_1|\,\mathrm{e} \\ &e\left(c_{g,k} \geq d_2, \theta_k\right) \\ &\qquad = \max\,(d_2 - \theta_k, 0)\,(3-5) \\ &e\left(d_1 \leq c_{g,k} \leq d_2, \theta_k\right) \\ &\qquad = \begin{cases} \theta_k - d_1 & if\ \theta_k > d_1 \\ d_1 - \theta_k & if\ \theta_k < d_2 \\ \theta_k & otherwise \end{cases} \end{aligned} \tag{5}$$

Secondly, when the group constraint is categorical data, the error of group constraint satisfaction is defined as shown in equation (6).

$$e\left(c_{g,k} = d_1, \theta_k\right) = \begin{cases} 0 & if\ \theta_k = d_1 \\ 1 & otherwise \end{cases} \tag{6}$$

Therefore, the importance of travel package components based on constraint satisfaction is defined as shown in equations (7) and (8).

$$\theta_k \succ_{c_{g,k}} \theta'_k \text{ iff } e\left(c_{g,k}, \theta_k\right) < e\left(c_{g,k}, \theta'_k\right) \tag{7}$$

$$\theta_k \approx_{c_{g,k}} \theta'_k \text{ iff } e\left(c_{g,k}, \theta_k\right) = e\left(c_{g,k}, \theta'_k\right) \tag{8}$$

That is, if the satisfaction error of θ_k for constraint k is less than the satisfaction error of θ'_k, the travel group prefers θ_k more. Additionally, if the satisfaction errors of θ_k and θ'_k for constraint k are the same, then there is no difference in preference between θ_k and θ'_k. For instance, let's assume among the group constraints, the airplane price (*f_price*) is below \$600, and the A flight ticket is priced at \$610, while the B flight ticket is at \$620. In this case, the satisfaction error for the A flight ticket is $e(f\_price \leq \$600, A_{\$610}) = \$10$, and for the B flight ticket, it's $e(f\_price \leq \$600, B_{\$620}) = \$20$. Hence, $A_{\$610}$ is preferred over $B_{\$610}$. However, the difference in the satisfaction error is only 1, making the satisfaction error ranking too stringent. To address this issue, this study has adopted the concept of the indifference interval to better reflect the realistic situations of constraint satisfaction problems.

In this study, the indifference interval ($\delta_{g,k}$) for constraint k of group g is defined as shown in equation (9).

$$\delta_{g,k} = \begin{cases} min\left\{\left(c_{i,k} + \delta_{i,k}\right) - c_{g,k}\right\} & if\ c_{i,k} \leq d_1 \\ max\left\{c_{g,k} - \left(c_{i,k} + \delta_{i,k}\right)\right\} & if\ c_{i,k} \geq d_1 \end{cases} \tag{9}$$

Here, $c_{g,k}$ and $c_{i,k}$ represent the constraint k of group g and the constraint k of an individual traveler i within the group, respectively. Moreover, $\delta_{g,k}$ and $\delta_{i,k}$ signify the indifference interval for constraint k of group g and the indifference interval for constraint k of an individual traveler i within the group. For instance, if customers A, B, and C within the group have the following airline price constraints and indifference intervals: "price $\leq$ 600, $\delta \leq 20$", "price $\leq$ 650, $\delta \leq 30$", and "price $\leq$ 500, $\delta \leq 100$" respectively, then the group's airline price constraint would be "price $\leq$ 500" and its indifference interval would be "$\delta \leq 100$".

Therefore, the importance of travel package components considering the indifference interval ($\delta_{g,k}$) for constraint k of group g is defined as shown in equation (10).

$$\begin{aligned} &\theta_k \succ_{c_{g,k}} \theta'_k iff \left|e\left(c_{g,k}, \theta'_k\right) - e\left(c_{g,k}, \theta_k\right)\right| > \delta_{g,k} \\ &\theta_k \approx_{c_{g,k}} \theta'_k iff \left|e\left(c_{g,k}, \theta'_k\right) - e\left(c_{g,k}, \theta_k\right)\right| < \delta_{g,k} \end{aligned} \tag{10}$$

D. PHASE 3: FILTERING BASED ON INDIVIDUAL TRAVELER APPROXIMATE CONSTRAINT SATISFACTION

After Phase 2, if the recommendation process is halted, there could be individual travelers who become marginalized due to their passive activities or low frequency of expression in the community. Inactive members often leave the group if their needs are not met and neither positive nor negative reactions are displayed. When selecting a group travel package, it is crucial to consider the preferences expressed as constraints by each member holistically. Thus, the third phase of GRec_Tr ensures that the satisfaction levels of specific individual members within the group don't plummet excessively. This phase consists of two stages: calculating the dissatisfaction levels of each member towards the candidate recommended travel packages and filtering out candidates that have significant dissatisfaction levels for members.

In the first stage, the error of constraint satisfaction, excluding the indifference interval for each recommended travel package, is calculated. The total error for individual traveler i in group g concerning destination j is calculated as shown in equation (11).

$$\sum e(c^j_{g_i,k}) \tag{11}$$

In essence, the total error represents the degree of dissatisfaction of individual traveler i within group g concerning package component θ_k under constraint condition $c_{gi,k}$.

In the second stage, the set of candidate recommendations is refined by excluding travel packages with high dissatisfaction based on the error of constraint satisfaction of individual travelers. The total error of traveler i in group g ($\sum e(c^j_{g_i,k})$) is sorted, and destinations j with the highest total errors are sequentially excluded until only one package remains for a single destination.

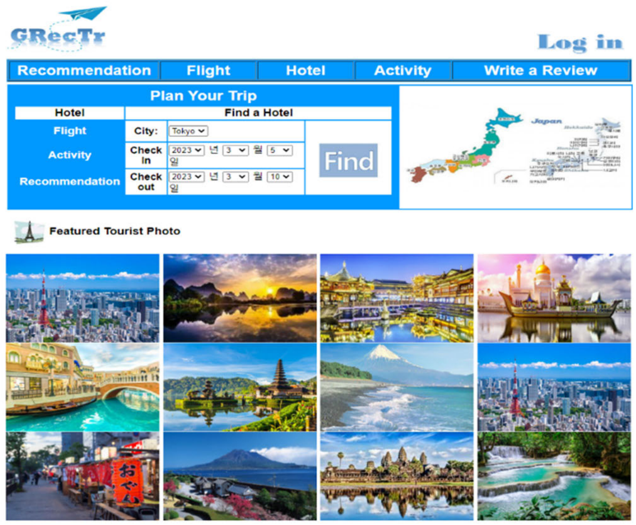

FIGURE 3. A prototype of GRec_Tr.

IV. EXPERIMENTAL RESULTS

A. INTRODUCTION

In order to conduct the experiment, a web-based prototype of the GRec_Tr travel recommendation system was developed, utilizing Microsoft Access and the Microsoft IIS web server, as shown in FIGURE 3. Communication with the database was facilitated using a standard ODBC interface.

For comparative analysis, we implemented benchmark systems that omit certain processes from GRec_Tr. In this study, two benchmark systems were developed, both based on the principles of group and individual traveler approximate constraint satisfaction filtering in travel recommendations.

The first benchmark system employs group approximate constraint satisfaction filtering, generating candidate travel destinations through CF-based filtering and recommending travel packages that meet the group's approximate constraints, including the indifference interval. However, this system does not consider the satisfaction of individual traveler constraints. The second benchmark system focuses on individual traveler approximate constraint satisfaction filtering. It constructs candidate travel packages for each destination that satisfy the group's constraints (excluding the indifference interval) through CF-based filtering and recommends packages fulfilling individual traveler constraints. This first benchmark system effectively omits GRec_Tr's third phase, the individual traveler approximate constraint satisfaction filtering process, allowing us to evaluate its impact on the overall system. Conversely, the second benchmark system, unlike GRec_Tr, excludes the indifference interval in setting individual and group constraints, aiming to assess how user satisfaction varies when comparing approximate constraint satisfaction filtering in GRec_Tr to traditional constraint satisfaction filtering.

Furthermore, to gauge user attitudes towards the recommendations provided by both GRec_Tr and the benchmark systems, a two-step survey was conducted, offering valuable insights into user preferences and satisfaction levels.

B. DATA COLLECTION

Data collection for this study spanned 3 weeks, from March 4th to March 24th, involving 210 individuals with overseas travel experience. The data gathering was structured in two phases. In the initial phase, respondents rated their preference for 53 popular Asian travel destinations on a 5-point scale. Additionally, they provided their constraints and indifference intervals concerning flights, hotels, vehicles, and attractions. In the final phase, using the collected data, travel destinations were recommended to each respondent through GRec_Tr and the benchmark systems, followed by feedback collection based on six evaluation indicators for each recommendation.

Demographic details of the respondents, as outlined in TABLE 1, reveal diverse backgrounds.

In the first phase, the gender distribution was 140 males (66.7%) and 70 females (33.3%), with age groups spanning from 20s to 60 and above. Regarding overseas travel experience in the last five years, the frequency varied from no travel to six times or more. The majority (59.5%) opted for free travel, with package tours and other options also represented. The main sources of travel information were internet searches (56.7%), followed by friends/relatives, travel agency websites, travel communities, and other sources. The demographic profile in the second phase showed a similar distribution, with 90 males (68.7%) and 41 females (31.3%). The age and travel experience distribution followed a comparable pattern to the first phase, with a slight increase in preference for free travel (64.9%) and internet search as the primary source of travel information (58.8%).

TABLE 1. Demographic information of the respondents.

		Phase 1	Phase 2
Gender	Male	140(66.7%)	90(68.7%)
	Female	70(33.3%)	41(31.3%)
Age	20s	50(23.8%)	35(26.7%)
	30s	37(17.6%)	20(15.3%)
	40s	48(22.9%)	33(25.2%)
	50s	62(29.5%)	36(27.5%)
	60 and above	13(6.2%)	7(5.3%)
Overseas travel experience in the last 5years	0	28(13.3%)	16(12.2%)
	1	46(21.9%)	28(21.4%)
	2	41(19.5%)	22(16.8%)
	3	32(15.2%)	22(16.8%)
	4	9(4.3%)	8(6.1%)
	5	12(5.7%)	6(4.6%)
	6 or more	42(20%)	29(22.1%)
Travel type	None	16(7.6%)	7(5.3%)
	Free travel	125(59.5%)	85(64.9%)
	Package tours	69(32.9%)	39(29.8%)
Source of travel information	friends/relatives	48(22.9%)	30(22.9%)
	internet search	119(56.7%)	77(58.8%)
	travel agency websites	14(6.7%)	10(7.6%)
	travel communities	16(7.6%)	9(6.9%)
	other sources	13(6.2%)	5(3.8%)
Total		210	131(%)

C. EVALUATION METRICS

Travel recommendation systems are designed to provide personalized recommendations to aid travelers in their decision-making process. Commonly, these systems are evaluated based on the performance of the recommendation results and the assessment of user attitudes influenced by the recommendation method. Numerous studies have used metrics like Mean Absolute Error (MAE), Recall, Precision, or the F1 score to measure the accuracy of recommendation systems [29], [57], [58], [59]. However, for travel recommendation systems, which typically suggest complex travel packages, these traditional metrics are less applicable, as they are primarily designed to assess singular items.

In our study, we evaluated the effectiveness of both the proposed GRec_Tr system and the benchmark systems. As detailed in TABLE 2, we assessed user attitudes towards the recommendations on a 5-point scale, ranging from 'Strongly Agree' to 'Strongly Disagree'.

The criteria for this assessment included relevance, novelty, unexpectedness, serendipity, usefulness, and user satisfaction. These criteria were chosen based on the work of previous researchers in the field [8], [19], [58], ensuring a comprehensive evaluation that goes beyond traditional metrics to reflect the complex nature of travel package recommendations.

D. EXPERIMENTAL RESULTS AND DISCUSSION

In the context of the COVID-19 environment, where travelers have shown a preference for small group package tours, typically consisting of 3 to 5 people, this study aimed to compare the recommendation results of our proposed GRec_Tr system with the benchmark systems (GRec_Tr/Simple, GRec_Tr/Strict). We assigned group sizes of 3, 4, and 5 to

TABLE 2. Evaluation metrics.

Metrics	Evaluation
Relevance	The recommended travel package aligns with my interests
Novelty	The travel package recommended to me is innovative or fresh
Unexpectedness	The item recommended to me is surprising or unexpected
Serendipity	The recommended travel package offers a delightful surprise, akin to unexpected good fortune
Usefulness	The suggested travel package aligns well with my preferences
User Satisfaction	I am satisfied with the recommended package

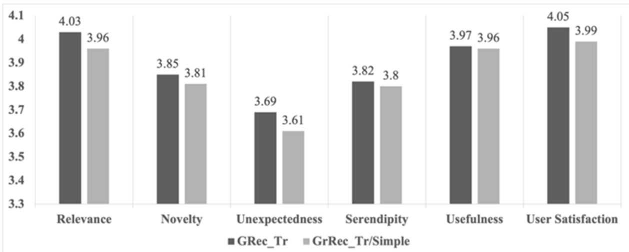

FIGURE 4. **The impact of traveler approximate constraint satisfaction-based filtering (Group Size = 3).**

the 210 respondents for this purpose. The composition of each respondent's travel group was randomly determined, with different group members assigned for the various group sizes. Consequently, each respondent provided evaluations on Relevance, Novelty, Unexpectedness, Serendipity, Usefulness, and User Satisfaction a total of nine times, once for each group size and system.

To assess the impact of traveler approximate constraint satisfaction-based filtering, we compared the evaluations between GRec_Tr and GRec_Tr/Simple. When examining groups of size 3 (as shown in FIGURE 4), the GRec_Tr system showed superior performance over GRec_Tr/Simple across all user attitudes, including relevance, novelty, unexpectedness, serendipity, usefulness, and user Satisfaction. However, in the case of groups of size 4 (FIGURE 5), GRec_Tr/Simple scored higher in terms of unexpectedness and serendipity. For groups of size 5 (FIGURE 6), GRec_Tr/Simple again had higher scores in unexpectedness.

To further delve into the potential significant differences in the evaluations of GRec_Tr and GRec_Tr/Simple, we conducted normality tests. Both the Kolmogorov-Smirnov and Shapiro-Wilk tests revealed that all evaluation metrics did not conform to normality, with a significance level of 0.000. Given these results, we proceeded with a non-parametric approach and performed the Mann-Whitney's U test to analyze the data. The findings of this test, as detailed in TABLE 3, showed that the approximate significance levels across all evaluation metrics and group sizes were greater than 0.05.

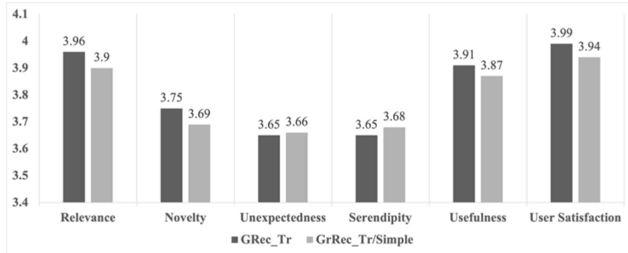

FIGURE 5. **The impact of traveler approximate constraint satisfaction-based filtering (Group Size = 4).**

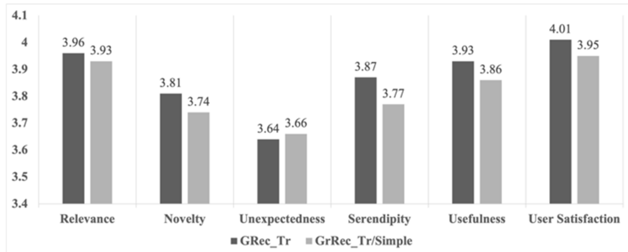

FIGURE 6. **The impact of traveler approximate constraint satisfaction-based filtering (Group Size = 5).**

TABLE 3. **Mann-whitney test results for evaluation metrics between GRec_Tr and GRec_Tr/Simple.**

	Group size	Relevance	Novelty	Unexpectedness	Serendipity	Usefulness	User Satisfaction
Mann-Whitney'U	3	9796	9971.5	9678.5	9997	10054.5	9721
	4	9855.5	9823.5	9984	9878	9844.5	9903
	5	9805	9589.5	9866.5	9457.5	9586.5	9654.5
Z	3	-0.618	-0.166	-0.603	-0.128	-0.042	-0.551
	4	-0.344	-0.388	-0.147	-0.305	-0.359	-0.273
	5	-0.208	-0.534	-0.112	-0.735	-0.541	-0.442
Approximate significance level	3	0.536	0.868	0.546	0.898	0.967	0.581
	4	0.731	0.698	0.883	0.76	0.719	0.785
	5	0.835	0.593	0.911	0.462	0.589	0.659

This outcome indicates that there is no statistically significant difference between the evaluations of GRec_Tr and GRec_Tr/Simple

The synthesis of our results, which aimed to verify the impact of traveler approximate constraint satisfaction-based filtering, reveals that GRec_Tr generally outperforms GRec_Tr/Simple in key aspects such as Relevance, Novelty, Usefulness, and User Satisfaction across different group sizes. This indicates that integrating the approximate constraints of individual travelers more accurately captures the preferences of group travelers, thereby enhancing the quality of recommendations. However, the very inclusion of individual travelers' approximate constraints may limit the scope of recommendations, confining them within the bounds of known preferences. This could explain why GRec_Tr scores lower in terms of unexpectedness and serendipity, as it potentially restricts the element of surprise or the discovery of unforeseen options in the recommendations.

To further explore the effect of group indifference on the recommendations, we compared the evaluations between GRec_Tr and GRec_Tr/Strict. The findings, as illustrated in FIGURE 7, show that for groups of size 3, GRec_Tr

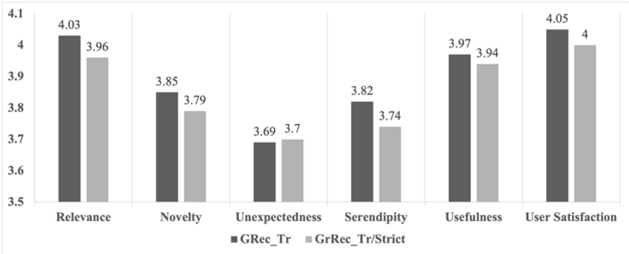

FIGURE 7. The impact of group indifference level (Group Size = 3).

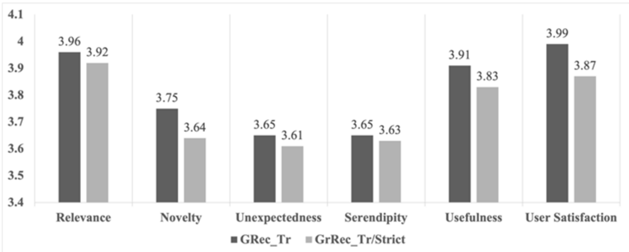

FIGURE 8. The impact of group indifference level (Group Size = 4).

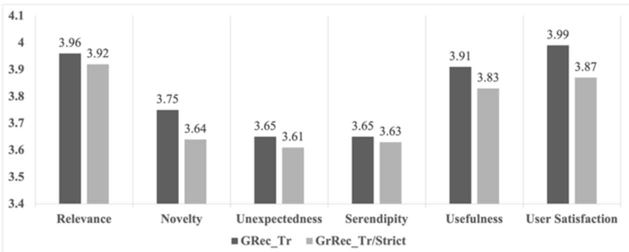

FIGURE 9. The impact of group indifference level (Group Size = 5).

achieved higher scores than GRec_Tr/Strict in relevance, novelty, serendipity, usefulness, and user satisfaction. However, GRec_Tr/Strict performed better in unexpectedness. In the context of groups consisting of 4 members, as depicted in FIGURE 8, GRec_Tr surpassed GRec_Tr/Strict in all user attitudes. Additionally, for larger groups of size 5 (FIGURE 9), GRec_Tr continued to score higher in relevance, novelty, serendipity, usefulness, and user satisfaction, while GRec_Tr/Strict maintained a lead in unexpectedness.

In synthesizing the results to assess the impact of group indifference, it becomes evident that GRec_Tr generally outperforms GRec_Tr/Strict in all group sizes in terms of relevance, novelty, serendipity, usefulness, and user satisfaction. This pattern suggests that using a filtering approach based on approximate constraint satisfaction, which accounts for levels of indifference, significantly enhances the quality of recommendations when compared to traditional constraint satisfaction-based filtering. The implication is that overly strict adherence to group constraints narrows the preference range considered by individual travelers, which in turn can diminish the quality of the recommendations. This finding underscores the importance of accommodating a certain degree of flexibility or 'indifference' in group constraints to ensure a broader range of high-quality recommendations.

TABLE 4. Mann-whitney test results for evaluation metrics between GRec_Tr and GRec_Tr/Strict.

	Group size	Relevance	Novelty	Unexpectedness	Serendipity	Usefulness	User Satisfaction
Mann-Whitney'U	3	9742.0	9901.5	10027.0	9691.0	10006.0	9941.0
	4	9919.5	9558.0	9930.0	9987.5	9645.5	9588.5
	5	9762.0	9816.0	9666.5	9620.5	9910.0	9913.5
Z	3	-0.518	-0.272	-0.082	-0.590	-0.115	-0.216
	4	-0.247	-0.787	-0.228	-0.141	-0.660	-0.750
	5	-0.274	-0.190	-0.414	-0.487	-0.047	-0.042
Approximate significance level	3	0.605	0.786	0.934	0.555	0.908	0.829
	4	0.805	0.432	0.820	0.888	0.510	0.453
	5	0.784	0.850	0.679	0.626	0.963	0.967

TABLE 5. Kruskal-wallis test results by evaluation metrics and group size (GRec_Tr).

	Kruskal-Wallis' H	Degree of Freedom	Approximate Significance Level
Relevance	0.456	2	0.796
Novelty	0.509	2	0.775
Unexpectedness	0.205	2	0.902
Serendipity	2.619	2	0.270
Usefulness	0.117	2	0.943
User Satisfaction	0.182	2	0.913

Furthermore, to determine if there were any significant differences in the assessments between GRec_Tr and GRec_Tr/Strict, an in-depth analysis was conducted. This included the implementation of normality tests, namely the Kolmogorov-Smirnov and Shapiro-Wilk tests. These tests indicated that the evaluation metrics did not follow a normal distribution, as all showed a significance level of 0.000. Consequently, to delve deeper into these observations, the study utilized the non-parametric Mann-Whitney's U test. The results from this test, as presented in TABLE 4, showed that the approximate significance level was above 0.05 across all metrics and group sizes. This outcome implies that there are no statistically significant differences between the evaluations of GRec_Tr and GRec_Tr/Strict.

In the next phase of our analysis, we aimed to determine whether the evaluations of GRec_Tr varied based on group size. For this purpose, we employed the non-parametric Kruskal-Wallis test to assess differences in evaluation metrics across different group sizes. The outcomes of this analysis, as detailed in TABLE 5, revealed that the approximate significance levels were all above 0.05. This indicates that there are no statistically significant differences in the evaluation metrics relative to group size. Such a finding implies that the size of the group does not substantially affect individual preferences within the context of our travel recommendation system.

This study's findings underscore the efficacy of the proposed GRec_Tr system, highlighting how individual constraint satisfaction significantly impacts the effectiveness of group travel recommendations. Moreover, it becomes clear

FIGURE 10. Results of improving individual travelers' Dissatisfaction.

that the level of indifference applied to group approximate constraints plays a pivotal role in shaping these recommendations. GRec_Tr, which is built upon the principles of collaborative filtering and constraint satisfaction, benefits from repeated use. Each usage contributes to the accumulation and refinement of user preference data. As a result, the more frequently GRec_Tr is utilized, the better it becomes at aligning its recommendations with user preferences. This iterative learning process leads us to anticipate high evaluations in crucial aspects such as relevance, novelty, usefulness, and user satisfaction.

The study also focused on quantifying the extent to which the proposed GRec_Tr method reduces individual travelers' dissatisfaction. As demonstrated in FIGURE 10, the results indicate significant improvements across various group sizes. For groups consisting of 3 members, the average dissatisfaction improvement was observed to be 60 for flight prices, 20.4 for hotel prices, and 24.4 for activity prices. In groups of 4 members, these improvements were more pronounced, with flight prices showing an average dissatisfaction reduction of 86.1, hotel prices 26.8, and activity prices 32. Lastly, for groups comprising 5 members, the dissatisfaction improvement was even higher, averaging 93.4 for flight prices, 27.1 for hotel prices, and 32.8 for activity prices. These results clearly demonstrate that the GRec_Tr system not only significantly minimizes individual traveler dissatisfaction but also substantially enhances the overall quality of the travel recommendations.

V. CONCLUSION

Generally, consumer purchases are influenced by the opinions of others or word-of-mouth (WOM) [60]. According to McKinsey survey, word-of-mouth marketing generates more than twice the sales of paid advertising [61]. In this study, the proposed group travel recommender system can design travel products suitable for group travelers' preferences using their preference and behavior data. In other words, the proposed system automates the word-of-moth effect, providing existing travelers with positive experiences. Therefore, our proposed method can enhance word-of-mouth, leading to increased sales. To significantly enhance the travel experience of groups, it is crucial to meticulously analyze their travel patterns and provide travel planning services that are specifically tailored to their needs, with an emphasis on continuous learning and improvement to elevate group satisfaction. This involves a deep understanding of various aspects of group travel preferences, including destination choices and budget considerations. Additionally, it requires offering personalized travel packages that comprehensively cover aspects like flights, hotels, shopping, events, and shows. While the domain of group travel recommendation systems is actively evolving, many existing systems still primarily focus on aggregating travel products for individual travelers, often overlooking the unique requirements of group travel. Our study addresses this gap by introducing a system designed to meet the specific needs of group travelers.

In this study, we introduced an innovative approach that combines Collaborative Filtering (CF) for destination recommendations with the concept of modeling group requirements as constraints. This approach facilitated the automation of the group decision-making process, culminating in the creation of the GRec_Tr system. We tailored the CF method to cater specifically to the dynamics of group travel rather than individual preferences, applying it to recommend travel destinations. Further, we articulated individual preferences and requirements as constraints within the system, incorporating a degree of flexibility to achieve consensus among group members. This method, known as the group approximate constraint satisfaction process, was instrumental in recommending comprehensive travel packages, including elements like flights, hotels, and activities. Consequently, the GRec_Tr system proposed in our study stands as a robust tool for planning group travel services, adeptly aligning with the diverse preferences of group travelers by analyzing their patterns and predilections.

Our research carries significant academic and practical implications. First and foremost, the proposed method demonstrates its effectiveness in assisting group travelers to find destinations, flights, hotels, and activities that align with their specific preferences. This capability is instrumental in enhancing the overall travel experience, consequently leading to heightened traveler satisfaction. Secondly, this method offers a time-saving advantage for travelers in planning their trips, streamlining the typically cumbersome process. Moreover, it provides an opportunity for travel agencies to increase traveler satisfaction, which can, in turn, lead to a boost in sales of their travel products. This positive feedback loop has the potential to cultivate a more robust travel ecosystem. Thirdly, while traditional Collaborative Filtering (CF) based group recommendation systems tend to focus on recommending single domain products, our system overcomes this limitation by concurrently recommending composite products, such as hotels, flight tickets, and attractions. By combining CF-based recommendations with group approximate constraint satisfaction, our travel recommendation system integrates various travel components into cohesive packages. This novel approach not only enhances the utility of CF-based systems but also opens new pathways for their application in more complex, multi-faceted domains.

While our research has yielded promising results, it is important to acknowledge certain limitations. First, the study was based on a relatively small data set, which may restrict the broader applicability of our findings. In this study, if we had measured performance using only the accuracy metrics commonly used in recommender system research, it would have been possible to evaluate using publicly available large-scale data. However, the six performance metrics measured in this study can only be evaluated through surveys of users who used the system, limiting the recruitment of experimental subjects. Future research would benefit from employing larger sample sizes to enhance the generalizability of user evaluations regarding the proposed method. Second, our study focused on travel destinations that had already been evaluated by users. This approach presents a challenge in recommending unreviewed or unrated destinations. To address this issue, we conducted a survey on preferences and constraints for new users of the system. However, this does not fundamentally solve the cold-start problem, which involves providing recommendations when there is no existing preference data for the user. Therefore, this remains an area to be addressed. Third, the GRec_Tr system relies on users to specify their own constraints and indifference levels. However, to minimize user effort and improve usability, future developments should explore algorithms capable of automatically deducing these constraints and levels of indifference from extensive, historical travel-related data. Lastly, it is necessary to provide personalized Points of Interest (POI) at the travel destination [62], [63]. Recently, significant advancements have been made in POI recommendation for travelers, thanks to the ability to collect data such as travelers' movement paths, time, and weather using various sensors embedded in smartphones [64]. However, research on POI recommendation for group travelers is still lacking. Therefore, future research will focus on developing a POI recommendation system suitable for group travelers' preferences and contextual information.

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