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ORIGINAL PAPER

A Comprehensive Survey on Travel Recommender Systems

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Abstract
Travelling is a combination of journey, transportation, travel-time, accommodation, weather, events, and other aspects which are likely to be experienced by most of the people at some point in their life. To enhance such experience, we generally look for assistance in planning a tour. Today, the information available on tourism-related aspects on the Internet is boundless and exploring suitable travel package/product/service may be time-consuming. A recommender system (RS) can assist for various tour-related queries such as top destinations for summer vacation, preferable climate conditions for tracking, the fastest way to transport, or photography assistance for specific destinations. In this survey, we have presented a pervasive review on travel and associated factors such as hotels, restaurants, tourism package and planning, and attractions; we have also tailored recommendations on a tourist's diverse requirements such as food, transportation, photography, outfits, safety, and seasonal preferences. We have classified travel-based RSs and presented selection criteria, features, and technical aspects with datasets, methods, and results. We have briefly supplemented research articles from diverse facets; various frameworks for a travel-based RS are discussed. We believe our survey would introduce a state-of-the-art travel RS; it may be utilized to solve the existing limitations and extend its applicability.

1 Introduction

Most of the individuals move between various geographical locations at some point in their life. Such a movement, also known as a trip, may be within local areas on a routine basis or on the global extension for a longer period of time which is likely to include short accommodation facilities such as hotels and restaurants. The purpose of travelling may vary from person-to-person, for example, business meetings, adventure, events, leisure, migration, research travel, or because some people wish to pursue the wanderlust. Such travellers give rise to the economy of organizing communities; they also provide employment to local as well as global businesses. Goeldner et al. [1] identified tourist, business supplying goods and services to tourists, host community and its government to be the perspectives of tourism; they defined tourism as "the science, art, and business of attracting visitors, transporting them, accommodating them, and graciously catering to their needs and wants". The tourism industry has grown on a large scale in the past many years and numerous travel services have been provided physically as well as virtually. Concerning the development of tourism, Gunn et al. [2] introduced five functional groups, namely, attractions, services and facilities, transportation, information and direction, and tourists. These aspects have been explored by many tourism-based service providers. However, the larger the number of service providers, the more difficult it becomes to identify and select a suitable travel plan. In order to reduce the number of efforts that an individual needs to put on identifying the right travel plan, recommender systems (RSs) have been developed. An RS may be considered as a subclass of information filtering system which predicts an individual's preferences and suggests a list of suitable options [3]; the suggestions generated by such a system may interest to a particular user [4, 5]. This article presents recommendations for tourism and parallel factors; from a wider perspective, the associated aspects have been explored to justify the requirement of tourism-based RSs.

In the tourism industry, transportation, accommodation, food services, attractions, events, adventure and outdoor recreation, entertainment, travel trade, and tourism services have been considered as the operating sectors [1]. These crucial sectors are responsible for tourism development. Earlier, the

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conventional travel plans were generally selected based on the experience of friends or relatives or they were chosen by the travel agents, whereas today, people have a rich set of digital resources available. People can evaluate the destined places in terms of the journey, stay, food, or events with the help of others' reviews, photographs, ratings, blogs, and other public views. However, with an increase in the number of digital sources, manual analysis of available options has become more difficult and time-consuming. It has elevated the requirement of personalized recommendations where a system is expected to learn the user's choices by examining various aspects in terms of implicit and explicit feedback and provide useful suggestions. These suggestions may be concerning different travel services such as hotels, restaurants, or places to be visited, events to be attended, or regarding foods, beverages, or other dish items. For a user who had visited various heritage sites in his/her past experiences, suggesting to visit a museum may be an example of personalized recommendation; a non-personalized recommendation may provide top-10 holiday destinations for summer. Considering various services, users are likely to have a general expectation of receiving filtered options with the most relevant information; for such purposes, various types of RSs have been developed which may be categorized into collaborative filtering (CF), content-based (CB), and hybrid approaches [6]. CF-based approaches analyze similar users and the items that have been liked by them and are recommended to the target user, whereas CB approaches learn about the items that were previously liked by the user and recommend similar items; combining these techniques provides hybrid approaches [3]. Here, in terms of a tourism RS, the items may be tour details, hotel facilities, restaurant preferences, or other specifications for potential travellers. CF uses the user-item interactions and hence, refers to people-to-people correlation [7], whereas CB uses the attribute information of users and items [8]. However, both of these individual approaches encounter limitations. Data sparsity, i.e., having a large number of missing values, and cold-start problem, i.e., unavailability of sufficient values given by other users, are the main challenges in CF; CB approach reduces the novelty and diversity of the recommended items and it cannot address the cold-start problem for new users. Hence, the hybrid approach is used to overcome such issues; it is a combination of CF and CB methods which can utilize functionalities of both the approaches. Apart from the user-item interactions, knowledge-based RSs consider constraints and cases to generate recommendations whereas demographic RSs leverage user's demographic information; it may be combined with the context to provide context-based recommendations. Various additional information may further be used to enhance recommendations and hence, context-based, time-sensitive, location-based, and other social RSs have been developed under domain-specific approaches. The common operational and technical goals of an RS are identified to be relevance, novelty, serendipity, and diversity which must be considered while developing an RS with the business-centric goal of generating revenue [8].

Electronic tourism (e-tourism) has become an emerging platform for providing tour-related advisory. The interested users may ask for queries regarding the tourist destinations, travel packages, expenditure details, or time constraints and a list of points-of-interest (POIs) matching users' preferences gets recommended using e-tourism. It introduces the necessity of personalizing tourism. Many researchers have already explored different aspects of travel-based recommendations; for example, hotel recommendation based on users' blogs [9]; customer preference-based restaurant recommendation [10]; POI recommendation based on weather information [11]; customized travel package recommendation [12]; chat-based travel group recommendation [13]. Such RS frameworks may be developed for web-based and/or mobile-based applications. In e-tourism, selection of hotel, restaurant, activity, POI, or other attributes may be identified by carefully examining various aspects, their functionalities, and related contexts. Such selection criteria are useful to derive users' expectations and the importance of various attributes; also, the hosting authorities may improve their services based on these criteria for the expansion of their business. We have identified various selection attributes for tourism-related services and their impacts; their associations are briefly discussed. The main objective of this article is to understand the wide-spread of tourism-based RSs and their application domains. We have covered hotel accommodations, restaurants, travel packages, tourist attractions, and other travel-oriented factors such as food, outfits, climate, photography, and safety-based recommendations. We have also included a list of features from these domains and studied their significance; the implication of our survey is compared with the existing ones.

1.1 Significance of Our Survey

Tourism and tour-based products and services have been largely explored by many researchers. To identify the significance of our survey on travel RSs, we have studied existing surveys in various travel-related domains; a short survey on travel [14], largely surveyed mobile-based tourism recommendations [15–17], intelligence-based survey [18], and survey on food recommendations [19] have been studied. In Table 1, we have compared these surveys with our survey using various criteria.

For the remaining article, the RS approaches have been categorized into CF, CB, hybrid, and domain-specific techniques for individual tourism-based modules. The article is organized as follows: Sects. 2 and 3 provide hotel and restaurant recommendations, respectively; in each section, we have discussed diverse features responsible for the selection of respective modules, i.e., a hotel and a restaurant, and

Table 1 Comparative analysis of our survey with existing tourism-related surveys for various criteria

References	Criteria C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
[14]		✓	✓		✓		✓	✓							
[15]	✓	✓	✓		✓	✓	✓	✓	✓				✓		
[16]		✓	✓		✓			✓	✓						
[18]	✓	✓	✓		✓	✓	✓	✓	✓						
[17]	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓		✓
[20]		✓	✓	✓	✓		✓	✓	✓						
[19]	✓	✓	✓	✓	✓		✓			✓					
Our survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C1—features; C2—applications; C3—interfaces (web-based and mobile-based); C4—frameworks; C5—RS approaches; C6—hotel RSs; C7—restaurant RSs; C8—tourism package and planning RSs; C9—attraction RSs; C10—food and beverage RSs; C11—photography RSs; C12—outfits RSs; C13—transportation RSs, C14—safety RSs; C15—weather-based RSs

significance of such features has been provided. The tourism packages, planning, and group recommendations are given in Sect. 4 along with associated features whereas POIs corresponding to tourist attractions, museums, and other events are discussed in Sect. 5. A tour may not be only about the hotel that one stays at or the places he/she may visit; widespread considerations such as photography, outfits, food, climate, safety aspects, and other tourism-based itinerary recommendations are elaborated in Sect. 6. These sections are devoted to specific tour-related modules and summarization of the existing techniques, datasets used, and other relevant details are provided in respective sections. Analysis of various surveys and novelty of our survey are discussed. We have concluded our survey with remarks on future aspects in Sect. 7. A structural overview of the article is as given in Fig. 1.

2 Hotel Recommender Systems

Travelling from one place to another generally includes accommodating places such as hotels; [1] categorized hotels into full-service, limited-service, resort, and convention hotels. Customers choose resting places based on various factors such as room availability, comfort-level, locality, ratings, budget specifications, and other individual aspects. Previously, hotel selection and booking tasks were majorly performed offline, with the help of travel agents, or on arrival at the destination, however, the online market has emerged in past few years and travellers have been largely preferring hotel selection and booking online. Manually selecting an appropriate hotel is a time-consuming process; it requires analyzing available hotels, comparing them, and booking. This raises a requirement of personal assistance for hotel selection.

Online hotel booking has broadened its market in recent years. Marketing entities try to enhance their commercial value to attract potential travellers. This induces to develop an understanding of various dimensions and their impact on hotel selection; we have collectively grouped these features in Fig. 2. Many case studies have been conducted to identify the impact of such factors on hotel selection. Authors have considered various scenarios and diverse localities to analyze the influence of several features, for example, promenade and comfort were found to be crucial aspects for

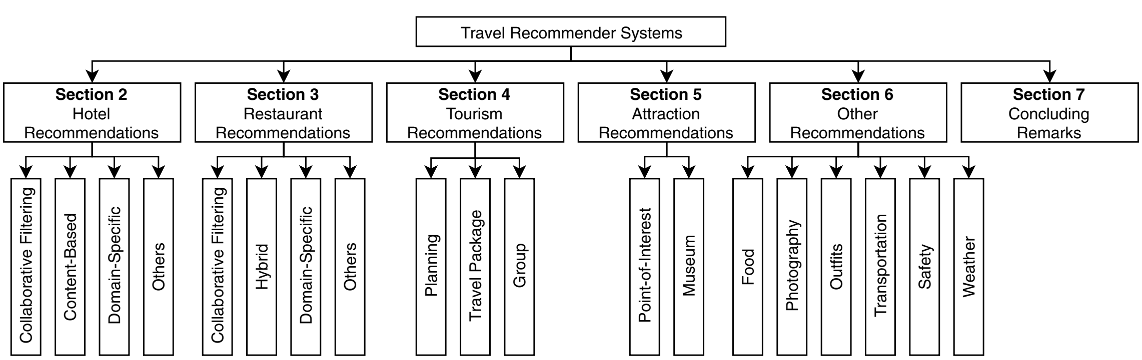
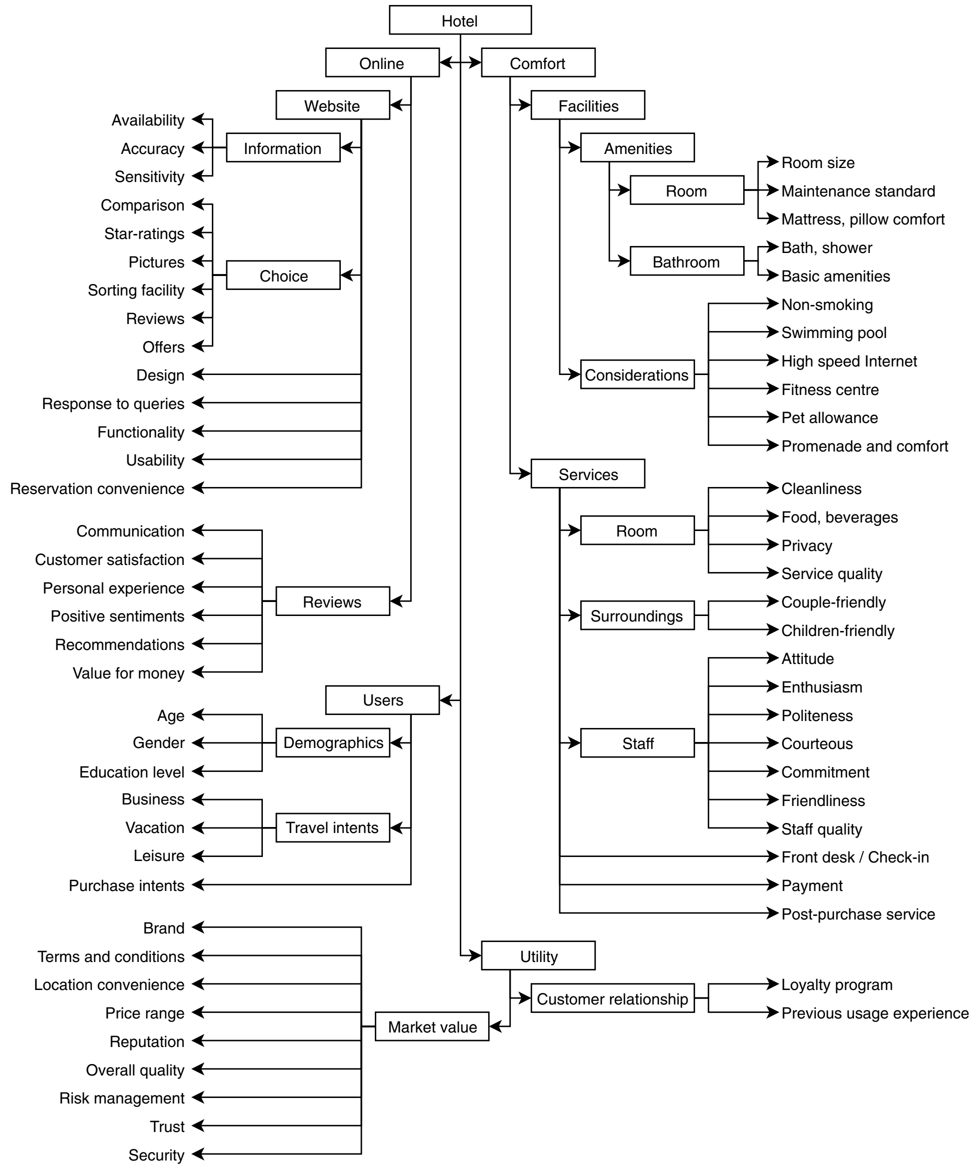


Fig. 1 A structural overview of travel recommender systems

Fig. 2 Various dimensions and features of hotel selection and recommendation



hotel selection in Tehran, Iran [21] whereas tangible dimension was identified as the best service predictor in Tehran hotels [22]; for customers travelling with children, safety was determined to be the salient aspect in hotel selection in Phuket [23]; Soulidou et al. [24] identified cleanliness as the most important factor in hotel selection for Greek customers. Also, it has been noted that intentions to book a hotel vary among customers; Van der Heijden et al. [25] stated the requirement of a higher degree of trust in online purchase intention as compared to the offline purchase. In the case of hotel booking intentions, customers' commitment, trust, and attitude were identified to have higher influence for low-habit customers [26] whereas brand image, perceived price, and perceived value were derived as the critical determinants that influenced the purchase intentions [27]. Development and growth of hotels are largely dependent on such factors and hence, self-analysis is mandatory for the managerial authorities, for example, [28] analyzed 21 business hotels and 20 boutique hotels in Bangkok and found the service quality to be relatively low in Thailand hotels. According to these case studies, hotels situated at different locations have variations in selection criteria; weights of such criteria may be determined for the targeted hotels, e.g., hotel location, quality of bed, comfort and equipment, service, value for money, and cleanliness criteria were weighted for tourists visiting Paris, France [29].

Figure 2 depicts various dimensions affecting hotel selection and features that can be used for hotel recommendations. An overview of such aspects is important to understand the implication of crucial factors and to examine features that should be taken into account for developing a hotel RS. We have considered the online availability of hotel data, users' expected features while visiting the hotel or those stated in reviews along with demographics of users to understand their significance in hotel recommendations. For a customer, value-for-money may be one of the most critical aspects; it determines the perceived value which may be affected by sentiments [30]. In the case of hotel accommodation, customers are likely to experience the perceived value after consumption of the service [31] or during different phases of the purchase process [32]. On the other hand, customer satisfaction is evaluated based on reactions on the consumption of services and it gets reflected in their reviews, star-ratings, loyalty and commitment towards the hotel or its brand, and further recommendations in terms of word-of-mouth; this dimension is a deciding factor for market value as well. Trust in the online context is helping the user through a smooth transition through the website with a reduced risk factor [33]. Also, the demographic factors of the users, such as their age-groups, gender, nationality, qualification, profession, and other socio-economic aspects are adopted to develop user profiles which can be used for further recommendations. Utilization of different features would be dependent on the objective of recommending a product or a service by identifying the targeted user and relevant item(s) which may interest him/her. In the case of hotel recommendation, correlations among various hotel features and targeted users' profiles may be regulated using various RS approaches as discussed in the subsequent sections.

2.1 Collaborative Filtering-Based Hotel Recocommendations

The criteria for selecting a hotel may vary based on users' requirements. User similarity may be identified to recommend hotels using the CF approach.

A hotel RS was proposed in [34] by considering the transition model of a user's hotel preference(s). Considering the reusability of a hotel room, authors created a preference transition network. They studied sales records of various hotels to generate relations among hotels. These relations were filtered based on co-occurrence and the preference transition between hotels was identified using the Mann-Whitney U test. The hotels were selected accordingly and ranked for recommendation purpose. Saga et al. [34] considered sales records of 172 hotels and 2227 customers who had stayed in hotels of Tokyo, Japan for more than twenty times. Authors specified that their proposed system provided qualitative recommendations.

Zulkefli and Baharudin [9] proposed a hotel RS based on travelogue blogs. Considering that a huge number of bloggers update about their trip to different places and share their experience, authors identified user profiles to get individual preferences on hotels. Also, the surrounding environment information was obtained by evaluating the blogs. The similarities were calculated to recommend top-N hotels. For this experiment, 50 blogs containing Langkawi, Cameron Highlands, and Kuala Lumpur areas of Malaysia were collected. Authors referred to the list of hotels from Agoda.com and Booking.com website. This setup was tested with ten active blog users; a chat box was provided in the proposed system to communicate with an online blogger friend(s).

Though pure CF-based travel recommendation approaches have been explored by considering overall ratings, [35] focused on the recommendations rated based on various dimensions and proposed for multi-criteria CF-based recommendations for the tourism sector. Authors applied an artificial intelligence (AI) method, i.e., adaptive neuro-fuzzy inference system (ANFIS), a clustering method, i.e., expectation maximization (EM), and dimensionality reduction, i.e., principal component analysis (PCA) for the hotel recommendation. They tried to overcome the multicollinearity problem of ANFIS by using PCA; the extracted fuzzy rules were utilized to predict unknown ratings and to reveal the level of user preferences on items' features; the membership functions (MFs) were applied in handling non-stochastic uncertainty emerging from vagueness and imprecision [35]. Authors also minimized and solved the overfitting problem by checking data [36, 37] and solved the sparsity problem in criteria ratings using the Pearson correlation coefficient (PCC). Top-N method [38] was used to recommend an item to the target user. Authors collected data of 1264 hotels, 85424 users and 7 criteria including value, room, location, cleanliness, check-in/front desk, service and business service aspects and an overall rating from TripAdvisor.com website. An overall rating was predicted using defuzzification and the accuracy of the proposed approach was evaluated using five-fold cross-validation; for Precision@k indicating recommended items for a user of size k, Precision@5 and Precision@7 were achieved to be 86.21 and 85.71, respectively, and 0.86 mean absolute error (MAE) was achieved.

A vector space for a fixed number of attributes may not be able to cover individuals' personal preferences and evaluation viewpoints. Considering the same, Zhang and Morimoto [39] proposed a method for automatically selecting appropriate vector space attributes from hotel review comments. The natural language text in comments was analyzed using latent Dirichlet allocation (LDA) and representative topics were extracted automatically; for each of the extracted topics, a sentiment value was derived. Using item-based CF in the proposed approach, similarities of hotels were calculated and a rating for the targeted hotel was predicted. The method was evaluated on a dataset containing 2256 reviews from TripAdvisor.com with an approximate 3.57% data density [39]. The pre-processing steps included tokenizing, stemming, and stop words removal using Stanford CoreNLP tool and various number of topics were selected for the experiment; an average of 0.67 MAE and 0.87 root-mean-square error (RMSE) was found for the proposed approach.

2.2 Content-Based Hotel Recommendations

One of the ways to analyze the significance of a hotel is by considering the reviews provided by visitors. Though in some cases, such reviews may be biased, other features may be exploited to analyze the usefulness of reviews and hotels may be recommended using the CB approach.

While a large amount of service RSs is available, O'Mahony and Smyth [40] proposed a review RS to suggest the helpfulness of various reviews of the given service; authors evaluated their approach using TripAdvisor.com hotel reviews. Four feature categories consisted of reputation, content, social, and sentiment features of review instances. Here, users could provide feedback on the reviews of TripAdvisor.com to show whether the reviews were found to be helpful. A supervised classification approach was used to classify review instances which had not received review helpfulness opinion. Authors collected reviews of TripAdvisor.com prior to April 2009 [40]; only the users having reviewed at least one of the hotels of Chicago or Las Vegas cities of US were selected. A total of 35802 reviews by 18849 users on 10782 hotels were collected; TripAdvisor.com reviews having at least five opinions were selected for training using three classifiers, JRip, J48, and Naïve Bayes. JRip provided an overall best performance; an area under ROC (AUC) was reported using ten-fold cross-validation. Authors analyzed the impact of various features on classification; reputation and sentiment turned out to be the most useful features. For recommending hotel reviews, two types of the most helpful reviews, highly-scored ($\geq$ 4-stars) and poorly-scored (< 4-stars) reviews were selected. Testing was carried out on hotels having at least five highly-scored reviews, i.e., 528 hotels and poorly-scored reviews, i.e., 224 hotels. The results indicated that 60% of the recommended reviews were helpful [40].

A review-based approach was proposed for the application of hotel searching using ensembled Naïve Bayes classifiers [41]. A total of 293 hotel reviews from 15 hotels having $\geq$ 3-stars of Phuket, Thailand were collected using TripAdvisor.com website. Authors created a vocabulary of 3070 words for the experiment and evaluated using different feature selection processes; Relief-F and Chi-Square outperformed. They ensembled these methods and provided a list of hotel names when a user queried keywords. The recommended list of hotels, ranked according to a probability using Naïve Bayes model, was compared with Boolean and Boyer-Moore searching methods; the proposed approach outperformed in terms of rank accuracy and search time [41].

2.3 Domain-Specific Hotel Recommendations

Hotel recommendations based on CF or CB may not be sufficient; users' contextual, location-based, or temporal information may be helpful for the domain-specific recommendations.

Individuals' profiles may not be built due to lack of historical data, however, the reviews may be exploited to characterize context groups for a hotel RS. Considering the cold start problem in hotel recommendations, a context-based hotel RS approach was proposed where an individual's intent for the trip, nationality, and preferences were collected for recommendation [42]. In the pre-processing steps, authors defined common traits of intent and nationality using noun and noun phrase features from the reviews; these features were then assigned a weight for each context; an opinion lexicon was built to analyze adjectives associated with features and to provide an orientation score to each feature. Features distinctive of several context groups might have different weights in each group; relevant feature weights were selected based on the user's preferences and a feature score was generated. The opinion lexicon was used to build an orientation score for each feature. By combining the features, respective wights, and orientations, each sentence was given a score; such sentence scores were combined to generate an overall score for each review which reflected the relative importance of the given review for the user. The final score for each hotel was calculated based on the reviews and an adjustment bias [42]. Authors followed [43] to measure relative user satisfaction and compared their proposed approach with the results of TripAdvisor.com and Venere.com websites. For the same, they experimented with 150 evaluations where users were asked to provide search parameters such as intent, nationality, aspect preferences, and a price range. The resulted recommendations included four suggestions from the proposed approach and the other two from the existing websites, i.e., TripAdvisor.com and Venere.com; the six recommended hotels were displayed in a random order to the users. Users were also asked to express their satisfaction for the suggested hotels and to rate all the recommended hotels on a scale of 1 to 5; the system also asked for the most influential aspect. Authors calculated the satisfaction/dissatisfaction results for both the countries, Germany and Italy; an improved satisfaction of 60.2% and a decreased dissatisfaction of 15.9% were achieved. [42] also carried out other comparative analysis and concluded that there was no strict correlation between how a review was identified and the rating given by the reviewer.

As mobile device usage has undergone immense growth, developing individuals' profiles based on mobile browsing behaviour has provided opportunities to many applications. Lin et al. [44] developed a mobile app to generate interest profiles of users for personalized context-based hotel recommendations. The app could allow users to search for hotels and browse hotel reviews; while reading hotel reviews, various gestures such as dragging, zooming in and zooming out were recorded. In this first phase, the hotel review paragraphs for which the user had shown interests were identified based on his/her gestures and the user's interest profile was constructed by applying text mining techniques on the preferred aspects of review content. In the second phase, a user's interest profile and aspect sentiments of hotel reviews were combined to generate hotel recommendations. Authors collected more than 5000 hotel reviews from TripAdvisor.com for hotels in Taipei, Taiwan, each containing 50 – 200 words. They used the hotel feature set containing 250 features derived from 988 annotated reviews as given in [45]; those features were classified into seven aspects: room, location, service, food, price/value, building, and facilities [44]. The sentiment score of each aspect was evaluated using a sentiment analysis tool, namely, Alchemy API, and a sentiment corpus [45, 46] and hotels with higher scores were recommended to the user. An experiment with 18 volunteers was carried out to evaluate the performance of the proposed approach; a website was created to allow users to rate the hotel based on its reviews. Here, the hotels were divided into two categories: inexpensive hotels, having room rates not higher than NT$3000 and expensive hotels, having room rates higher than NT$3000; each volunteer could select only one category and 10 randomly picked hotels from the selected category were displayed to the volunteer for evaluation. Precision and recall were measured for top-5 hotels and authors found that sentiment derived from textual data was more accurate than the ratings reported by the user. Also, Kendall's tau-b correlation coefficient showed that the proposed discriminating feature weight approach outperformed the average rating and the equal feature weight approaches. Lin et al. [44] concluded user preferences and reviewers' comments to be important factors for making good recommendations.

Al-Ghosseinet al. [47] addressed the sparsity problem in hotel recommendation and considered location-based social networks (LBSNs) to learn mobility patterns from hotel check-in data. Users generally select a destination to visit and then look for a hotel for accommodation. Authors tried to learn accessible destinations for users based on their past activities; here, the region preferences were more relevant than that for specific POI; the region size was dependent on hotel density. Mapping of check-ins, hotels, and users was carried out to recommend hotels using Bayesian personalized ranking (BPR) [48]. YFCC dataset [49] was used to experiment with 24 million check-ins performed by 32000 users. Al-Ghosseinet al. [47] trained the booking dataset with 80% data and the remaining 20% of the data was used for testing; performance of the proposed approach was measured using recall and normalized discounted cumulated gain (NDCG) metrics. Using various number of bookings for each user in the training set, the proposed cross-domain approach was compared with most popular hotels recommendation, content-based method, user-centred neighbourhood-based method, matrix factorization and BPR techniques. The cross-domain approach outperformed other techniques when the number of bookings for each user was less than or equal to 10 whereas BPR outperformed cross-domain approach for the number of booking greater than 30. Authors stated that the time dimension might play a vital role in the decision-making process.

2.4 Other Hotel Recommendations

Many hotel recommendations are found to be following reviews or similarity with the previous choices of individuals. Walek et al. [50] identified that hotel booking systems should have been providing a planning facility such that individuals might choose different activities and events in and/or around the targeted hotel. For the purpose of interconnecting hotels with places and corresponding activities and events around, an expert system was developed based on a questionnaire [51]. If-then rules were used from the knowledge base to determine the suitability of hotels and surrounding activities/events for individuals. In the first step, a questionnaire was defined for the purpose of evaluating suitability of hotel services and suitability of activities and events; type of stay and guest type were intended for both the evaluations; levels of interest in sporting and relaxation hotel services were intended for hotel services suitability whereas expected average distance of activities/events from hotel, average time duration of activities/events, and required level of guest rating of activities/events were intended for activities and events suitability. The questionnaire was displayed after the procedure of room and food reservation for the hotel. Walek et al. [50] introduced an expert system created with linguistic fuzzy logic controller (LFLC) tool [52] for defining suitable hotel services; it used center of gravity (COG) method for possible defuzzification. On the other hand, the definition of suitable activities and events was performed using if-then rules on a knowledge base and a database of POI, activities, and events. For all hotel services and activities as well as events, the levels of suitability were evaluated and visualized by the expert system and an individual could select an appropriate hotel.

While majority of the research works were carried out for hotel recommendation, Chu and Huang [53] proposed to predict hotel ratings by considering visual information in terms of hotel cover photos provided by hotel administrators and cultural differences of various users. For the experiment, authors collected hotel information such as name, address, and contact information; hotel photos; rating information such as rating items, user comments, and comment date; and user information including his/her country specifications. The data was collected from TripAdvisor.com, covering more than 1320000 unique users and more than 693000 user comments. The user's experience with the hotel was represented in terms of nine different rating items which were room, service, business service, cleanliness, check-in/front desk, overall rating, value, location, and sleep quality. They had considered UIUC dataset [54] and developed a crawler to collect cover photos and various metadata; majority of the hotels were found to be located in the United States or Europe. Based on the user location, the city name and corresponding country information were extracted too; most of the users were found to be coming from North America and Europe. Combining various information, Chu and Huang [53] constructed National Chung Cheng University (CCU) hotel dataset and analyzed if users had different preferences on rating items; whether travellers coming from different countries had different rating behaviours; classification of indoor and outdoor photos; detection of semantic concepts; and correlation between visual information and hotel ratings. Authors identified that hotels with outdoor cover photos had higher average score on location rating item whereas hotels with indoor cover photos had a higher average scores on room, service, cleanliness, overall rating, value, and sleep quality rating items. Authors also verified the effectiveness of cultural difference. They used user, hotel, date, price, nationality, comment, and visual concept vectors and applied a five-fold cross-validation scheme. Also, mean absolute deviation (MAD), MSE, and Pearson correlation metrics were employed to evaluate the performance of hotel rating prediction. By jointly considering all the vectors, overall rating prediction had achieved 0.821, 1.132, and 0.373 MAD, MSE, and Pearson correlation, respectively [53]; the distinctive judgements towards cleanliness and check-in/front desk were found in Japanese and Russian travellers, respectively. Authors also compared their proposed approach with latent aspect rating analysis model (LARAM) [55] and showed its effectiveness.

We have summarized the existing hotel RSs of various categories along with the features, methods, and data specifications in Table 2; results of these approaches have also been discussed.

3 Restaurant Recommender Systems

Food has been a crucial part of our everyday life, however, the approach towards consuming the food may differ among localities, cultures, personal interests, and other socio-economic aspects. A place where food is sold may be a food truck, a cafeteria, or a shop, i.e., a restaurant, in general. Selection of an appropriate restaurant may be a time-consuming task as there is a vast number of food suppliers available in the market. On the other hand, various attributes affect the selection of an appropriate restaurant as well as patronage intentions of customers; for example, service quality in terms of intangibles, tangibles, and food were identified to be influencing revisiting intentions of foreign travellers in Korean restaurants [56]; customers' susceptibility to emotional contagion was found to be one of the major aspects influencing tipping behaviour in restaurants of Turkey [57]; personal aspects of the waiter/waitress such as tidy clothes, clean nails, polite behaviour, general attitude, and respecting customers' privacy, and functional practices such as service speed, hygiene practices while serving, and knowledge of ingredients of the menu items, were found to be impacting on customer satisfaction [58]. Also, the motives behind visiting a restaurant are important to analyze; managerial implications might be provided in accordance with such motives [59]. In restaurant services, customers' comfort and satisfaction are cautiously supervised; Ariffin et al. [60] had identified the atmospheric element of style to be contributing to the customer behaviours in various ways.

For travellers, who may not have sufficient information about suitable restaurants, reviews and ratings may become the deciding factors on the selection of restaurants. However, the reliability of these reviews is a prime concern. There are many websites and mobile applications based on the restaurant details which look forward to spreading their market; to attract users in bulk, they use various schemes such as offers or financial incentives on inviting other people to download and use such applications. Such rewards may induce fake reviews [61]. Also, people have different ways to express their support and revenge. Such emotional obligations may lead to improvised reviews and ratings; decisions based on such biased comments may lead to disappointment and annoyance. Trolling has currently become a trend on social networking sites where individuals distract readers into quarrels and provoke towards emotional responses. [62] studied how trolling encounters had impacted e-tourism worldwide. Hence, receiving an unbiased recommendation is highly desired while visiting different places. This introduces the requirement of a restaurant RS which may learn individuals' preferences and suggest the most suitable places to explore. Brand reputation is essential for a restaurant to be

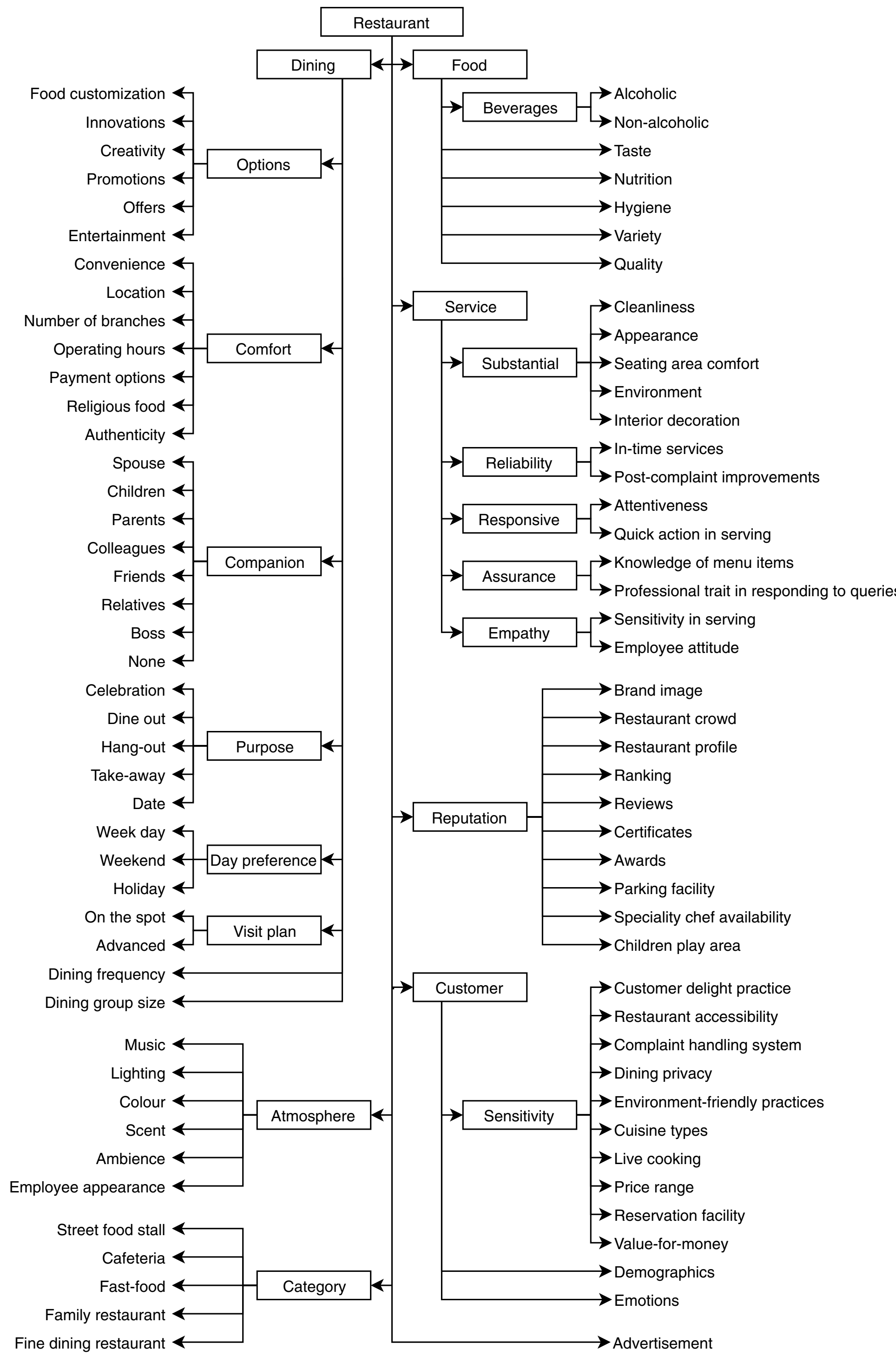
Table 2 Summary of hotel recommender systems

References	Category	Features	Methods	Data specifications	Results
[34]	Model-based CF	Reusability, preference transition, rating	Preference transition model	172 hotels of Tokyo, 2227 customers	Qualitative recommendations
[9]	CF	User preference, hotel surroundings	Cosine similarity	50 blogs on Langkawi, Cameron Highlands, Kuala Lumpur; testing with 10 active bloggers	Unspecified
[35]	Multi-criteria CF	Value, room, location, cleanliness, check-in, service, business service	ANFIS, EM, PCA; MF	1264 hotels, 85424 users from TripAdvisor.com; five-fold cross-validation	86.21 Precision@5, 85.71 Precision@7, 0.86 MAE
[39]	Item-based CF	Review comments	LDA	2256 reviews from TripAdvisor.com; 3.57% data density	0.67 MAE, 0.87 RMSE
[40]	CB	Reputation, content, social, sentiment of reviews	JRip, J48, Naïve Bayes	35802 reviews, 18849 users, 10782 hotels from TripAdvisor.com; ten-fold cross-validation; testing with highly-scored reviews (528 hotels), poorly-scored reviews (224 hotels)	60% of recommended reviews helpful
[41]	CB	Reviews	Ensembled Naïve Bayes	293 reviews, 15 hotels of Phuket from TripAdvisor.com	Outperformed rank accuracy, search time
[42]	Context-based	Trip intent, nationality, user preference	Feature weight assignment, opinion lexicon	150 users	60.2% satisfaction, 15.9% dissatisfaction
[44]	Context-based (mobile app)	Reviews; room, location, service, food, price/value, building, facilities	Alchemy API, sentiment corpus	5000 reviews for Taipei hotels from TripAdvisor.com	Higher Precision@5; derived sentiment more accurate than user's ratings
[47]	Location-based	Check-in	Cross-domain, BPR	YFCC [49]; 24 million check-ins by 32000 users; 80% training, 20% testing	Recall, NDCG; cross-domain outperformed (bookings ≤ 10), BPR outperformed (bookings > 30)

recommended to potential customers; the facilities and services provided at the restaurant are evaluated by customers as well as various authorities. Such authorities may provide certificates or awards to the restaurant which can upgrade its brand image in the market, patronage behaviour and loyalty from customers, and raise in the number of recommendations to users.

Figure 3 gives a brief overview of various dimensions which may be considered in selecting a restaurant. Rhee et al. [63] examined different types of restaurants in one of their studies and found food attribute to be the most significant factor; the food priority is given here, along with available varieties and customization options. Service quality and adaptability are highly expected from the restaurant staff members. Depending upon the restaurant type, dining may

Fig. 3 Various features of restaurant recommender systems



vary by means of the targeted customers, their expectations, and responsiveness of the employees in handling them. We include various aspects of dining such as comfort-levels, intents behind dining, preferences and planning for specific dining, the dining companion, and frequency of dining. These features are helpful in identifying user characteristics; other demographics can also be exploited to create user profiles. Such details may be utilized in recommending restaurants. We describe various restaurant RSs and respective features used for the purpose.

3.1 Collaborative Filtering-Based Restaurant Recommendations

New users generally encounter cold start problem in a CF-based approach. For a CF-based restaurant RS, Wen-ying and Guo-ming [64] developed an approach to deal with new users by minimizing the number of inputs that they were expected to provide during the cold start phase. In the proposed approach, authors used a rule-based algorithm to overcome the issue of the cold start phase and combined it with user-based and context-based CF algorithms in the user behaviour data analysis phase. Considering that users' demands could change on short-term preferences such as cooking category or time and place choice, and long-term preferences such as price range or the environment. Hence, users' profile information such as gender, age, and mobile device information such as the operating system, phone model, software were collected; the contextual information included location, weather, time, season information; restaurant information consisted of category, features, and basic information; and user's log records including ratings and interaction data were collected. The recommendations were carried out according to the same contexts of ratings and nearest neighbours of ratings. This framework provided effective and valuable recommendations.

Users having same movement areas are likely to have spot information which may be useful for others, however, evaluation of the commonality of such movement areas might not be useful if the user goes away from an unfamiliar location. To resolve such problem, Hasegawa and Hayashi [65] developed a spot RS which was aimed to be available in the familiar as well as new areas and demonstrated it using a restaurant RS application. Authors explored the spot-visiting histories of other users who belonged to specific locations and the target user's current location was taken into consideration. For recommending restaurants, various spot genres, i.e., classification of the restaurant, were selected. The spot information was collected from Tabelog.com and experiments were carried out with two users and 11 participants to show the usefulness of the proposed approach.

According to Sun et al. [66], selection of a restaurant might be influenced by several factors such as check-in locations, recommendations by friends, popularity based on different regions, purchase behaviour and traffic conditions around the restaurant, and dynamic mobility behaviours of users. For exploiting such multi-source information, authors developed a probabilistic factor analysis framework, named RMSQ-MF. This model considered three main aspects: personal interests in restaurants, personal interests in the area around restaurants, i.e., user's region interest being similar to his/her friends', and social influence. The region popularity was identified using taxi drop-off and it was combined with the region information. For the experiment, authors considered data including users' profiles, ratings, friend lists, and restaurants' profiles from Yelp.com website covering Manhattan district. A total of 1000 out of 7115 restaurants were selected having the maximum distance using a greedy algorithm. Also, New York City taxi data were gathered for taxi drop-off information considering 11:00–13:30 and 17:30–20:00 h to be the lunch and dinner time period in Manhattan, respectively. The restaurant location and taxi customer drop-off location, in terms of longitude and latitude distance, were matched and a total of 21,684,273 taxi drop-off records were found for the 1000 restaurants. The proposed approach was compared against non-negative matrix factorization (NMF) [67], singular value decomposition (SVD) model-based SVD++ [68], BiasedMF [68], probabilistic matrix factorization (PMF) [69], and SocialMF [70]. Sun et al. [66] randomly selected 80% of data for training purpose with a different number of latent factors to test all the methods and the performance evaluation concluded that the proposed method had outperformed with average MAE and RMSE of 0.79 and 0.98, respectively.

A user-based CF approach was advanced for recommending restaurants based on user ratings and attributes [71]. The proposed approach was divided into three parts including user rating similarity in terms of average score factor and similarity confidence correction factor, user attributes similarity, and a combination of these similarities, based on which the proposed approach was carried out. The experiment included data of 627 restaurants and 46718 ratings given by 30081 users; the data was collected from dianping.com website which had covered the city of Guilin, China. The proposed approach was compared with traditional user-based CF using MAE and RMSE metrics.

3.2 Hybrid Restaurant Recommendations

An individual would prefer going to a restaurant based on various aspects such as time-constraint, surrounding locality, cuisine specification, price range, popularity, social influence, to name a few. A different kind of aspect may be termed as psychographics which may include personality-related attributes; an individual's attitude and aspirations may also be deciding factors while selecting a restaurant.

Katarya and Verma [72] considered similar attributes including lifestyle, interest, and personality of an individual to be predicted based on mobile usage pattern for recommending a restaurant. Authors also adopted demographic attributes such as age, gender and user's current location for the proposed mobile-based restaurant RS. They collected data from Foursquare.com website; the experiments including psychographic factor provided improved RMSE for community rating and check-in details.

To recommend a restaurant in a metropolitan such as Tangerang Selatan, Indonesia, Utama et al. [10] proposed for an application based on fuzzy logic and bubble sort approaches. Authors selected interest, location, and rating parameters for fuzzy logic which were the representations of product interest discovery [73], i.e., CF-based approach, geographic convenience [74], i.e., location-based approach, and users attention similarity [75], i.e., CB approach [76]. This experiment was evaluated for 12 restaurants with 77 respondents and the most suitable restaurant was recommended using bubble sort algorithm. This application also allowed the users to select dish item(s) from the menu and the place where they would like to sit.

Customer satisfaction has been a crucial task in any user-oriented service. For an RS to suggest a particular restaurant to a large number of users would require higher ratings on food, service, behaviour of the staff members, environment, and overall satisfaction. A comparative analysis was conducted for predicting restaurant satisfaction rating based on CF, CB, and hybrid approaches [77]. This experiment was conducted using a public database [78] which contained customer data including user's profile and characteristics with 20 attributes, restaurant data including various characteristics over 21 attributes, and rating data including customer satisfaction value ranging from 0 to 2, where 0 indicated unsatisfaction and 2 indicated satisfaction, for the restaurants that had been visited by the customers. Authors used a summation of ratings, i.e., satisfaction, food, and service; the total rating values ranged from 0 to 6 here, where 6 indicated being fully satisfied in all dimensions for the given restaurant. The data was pre-processed and five-fold cross-validation was applied to evaluate the performance of the approaches. Here, cluster analysis, similarity test, and weighted sum were combined for the CF approach, whereas regression was used for the CB approach; the proposed hybrid approach was a combination of these two techniques which received a mean of 0.064 and standard deviation (SD) of 1.294 along with MAE being the lowest, i.e., 1.032, among all the approaches.

Combining features of CF and CB approaches, item similarities and user similarities were found to recommend restaurant [79]. For the target user, recent item(s), i.e., the restaurant(s) that he/she had recently interacted with, was given as input and similar restaurants were found; the sorted restaurants were recommended. Similarly, users having similar taste of restaurants, as that of the target user, were selected; recent restaurant(s) interacted by the most similar user(s) was given to find item similarities as explained previously and the sorted restaurants were recommended to the target user. For this purpose, datasets were derived from an online restaurant directory service in Indonesia which included 67845 reviews and 83082 restaurant details [79]; authors used data from year 2014 to 2016 for training purpose while data of year 2017 for testing their approach. The comparison had shown F1-measure to be higher for restaurant similarity.

3.3 Domain-Specific Restaurant Recommendations

Customer satisfaction is a crucial task for any recommender system. While a large number of mobile-based context-aware services have utilized location-based approaches, Chu and Wu [80] also considered users' personal features for a mobile context-based restaurant recommendation. Authors developed a system which collected contextual information such as location, seasonal food information, and restaurant types including Taiwanese snacks, exotic cuisine, refreshments, and gourmet restaurants. The system allowed users to set their preferred time, eating habits, and other preferences; the restaurant information along with each user's preference information were transformed into vectors. This experiment was conducted with 33 users. Authors analyzed user satisfaction and quality of the system, information, and service in terms of mean and variance; the statistic for Cronbach's α was found to be greater than 0.7 indicating acceptability of the questionnaire used in this approach.

A location-based restaurant RS integrated with a mobile environment, namely My Eat!, was proposed [81]. Along with the location data, authors considered personalization and ubiquity [82] to enhance the dining experience of users. The check-in behaviours of users were studied and various details were extracted from Foursquare.com [83, 84]. The restaurant recommendation values were calculated by exempting any restaurant chain that might be liked by the user, i.e., different branches of the same restaurant were exempted, and a map view of the recommended restaurants was presented to the user on his/her mobile phone.

For a restaurant recommendation, Zeng et al. [85] exploited the mobile environment based on features of the user's preferences, i.e., the visited restaurants and location information. For the proposed approach, various restaurant features were considered using a user preference model and similarity between user and restaurant was calculated. Generally, people prefer going to the nearby restaurants, and hence, the distance between the user's current location and the restaurant was evaluated using GPS and Baidu map cloud service (BMCS). The calculated scores were used to suggest top-N restaurants. For the experiment, 107 restaurants were selected with 11 extracted features, viz. hot pot, grill, buffet dinner, fast food, Japanese food, seafood, noodle, duck soup, chicken soup, steak, and dumpling; six users participated and they clicked on the restaurant in the recommended list if they had visited it. A total of 209 such clicks were collected. The results indicated 89.5% selected restaurants ranked in top-5 with an average rank of 3.47 [85]; the case study revealed the effectiveness of the proposed approach.

3.4 Other Restaurant Recommendations

Today with increased usage of social media, a vast number of social network users would prefer to post their check-in details; such check-ins may be posted while visiting restaurants, hotels, or other events locally as well as globally. Facebook has been widely explored in terms of such regular check-in posts; it has millions of monthly active users. One of the popular applications for food ordering is Zomato which also has a huge number of active users. Taneja et al. [86] considered recommending restaurants to help travellers explore the trending landmarks during their trip; authors used Facebook check-ins and Zomato ratings for trend analysis and developed an app named as Travel Best. They identified the patterns followed by long-distance travellers by tracking their Facebook check-ins; the shortest route, the longest route, and the most frequently travelled route were visualized using a graph database, i.e., Neo4j. They also collected information about the nearby restaurants using Zomato and considered food quality, service, and ambience details to provide restaurant ratings. Based on the chosen location or route, suitable restaurants were recommended using opinion mining. The accuracy calculated for the proposed approach was found to be 60–70%.

Partial data has been largely considered as an issue in many application, however, a restaurant RS was developed by exploiting the incomplete rating details. Miao et al. [87] developed a system with preference queries on incomplete information (SI^{2}P) for friendly recommendations of a restaurant. A browser-server model was adopted with three functionalities: query submission, result explanation, and dataset interaction. The server side was provided with an extended PostgreSQL database where skyline and top-k domination (TKD) preference queries were applied on the incomplete data. Authors collected data from TripAdvisor.com website; users were allowed to specify a query via a single selection box; the query results were returned in a list and visualized by a map; the details of a restaurant could be found from the database using the query.

While considering aggregation approach reports received from a group of customers, the overall satisfaction may be high but it may be low at an individual level. To overcome such problems, Zhang et al. [88] combined group correlations and customer preferences. Authors proposed a method where the pre-processed data were transformed to be used for establishing customer group and then group correlations between customer and restaurant groups; multi-criteria weights were determined and similarity was calculated to obtain the most similar customer group for the target customer; the preferred restaurant group was hence obtained using degree of similarity; the overall ratings were predicted for recommending top-N restaurants. For 60 restaurants in New York, authors collected 6269 ratings given by 1945 customers from TripAdvisor.com with data sparsity to be more than 94.63%. To test the proposed approach, authors created a dataset containing customers having rated at least seven restaurants and named it as YM-7-7. The proposed model was compared against standard CF, multi-criteria CF, and clustering with multiple linear regression models. Using five-fold cross-validation, the proposed approach outperformed with RMSE and MAE of 0.262 and 0.134, respectively [88].

A travel itinerary recommendation was proposed [89] where authors used a genetic algorithm (GA) approach and modelled an orienteering problem (OP) [90, 91]. For the selected starting and ending points of a trip, random locations were included between them, provided that the total duration did not exceed the allowed maximum time. For lunch and dinner, the trip was expected to include two restaurants for the respective time. From the initialized chromosomes, i.e., the initial trip solution, the fittest were selected in the next phase and partially mapped crossover [92] was used followed by random mutation. For testing the approach, authors selected top-50 tourist attractions and top-20 local restaurants of Yogyakarta, Indonesia using TripAdvisor.com website. For a maximum of 15 hours of a trip, the GA parameters such as population size, crossover rate, and mutation rate were chosen to be 46, 0.72, and 0.27, respectively [89]. For one day-trip, various cases were examined in terms of rank and utility value; results suggested the effectiveness of the proposed approach.

In Table 3, we have given a summary of existing restaurant RSs belonging to different categories. We have also mentioned the features, methods, and data specifications along with the results.

4 Tourism Recommender Systems

Various tour packages are largely available in different forms. They may include transportation, visits to a list of destinations, restaurants, and hotel stays within a pre-defined schedule. Interested users may approach to travel agents; depending on the travel group size, tour intents, and other requirements, the agents may customize the tour or the users may be merged with other travel groups having similar interests. To customize such trips, users may constraint on different aspects of a tour or they may wish to plan a trip on

Table 3 Summary of restaurant recommender systems

References	Category	Features	Methods	Data specifications	Results
[64]	User-based, context-based CF	Contexts, user profiles, restaurant information	Rule-based	Unspecified	Effective and valuable recommendations
[65]	CF	Spot-visiting histories, location, spot genres	CF	2 users, 11 participants; data from Tabelog.com	Improved results than the existing spot RS
[66]	CF	User profile, ratings, friend lists, restaurant profile	CF	1000 restaurants from Yelp.com; 21684273 taxi drop-off records	0.79 MAE, 0.98 RMSE
[71]	User-based CF	Rating	CF	627 restaurants, 46718 ratings, 30081 users from dianping.com	Improved MAE, RMSE
[72]	Hybrid (mobile-based)	Lifestyle, interest, personality; age, gender, location	Hybrid	Data from Foursquare.com	Improved RMSE for community rating and check-in
[10]	Hybrid	Interest, location, rating	Fuzzy logic	12 restaurants, 77 respondents	Suitable restaurant recommendation
[77]	CF, CB, hybrid	Satisfaction, food, service	Cluster analysis, similarity test, weighted sum; regression model	Public database [78] with customer, restaurant, rating contents; five-fold cross-validation	0.064 mean, 1.294 SD, 1.032 MAE
[79]	Hybrid	Reviews	Nearest neighbour	67845 reviews, 83082 restaurants from online restaurant directory	Higher F1-measure
[80]	Context-based	Location, seasonal food information, restaurant types	Client-server	33 users	Cronbach's α statistic greater than 0.7
[81]	Location-based	Check-in	Machine learning algorithm	Data from Foursquare.com	Map view presentation
[85]	Location-based	Home-made, 11 restaurant features	BMCS, Baidu Web Cloud Service (BWCS)	107 restaurants, 6 participants, 209 clicks	89.5% selected restaurants ranked in top-5; 3.47 average rank

their own. For planning a trip, individuals need to search for details of destinations, schedule routes and transportations, compare price, estimate timings, book tickets, register stays and other travel-related tasks. Hence, an assistance may be expected while performing such time-consuming activities. Various tourism-based recommendations aim at facilitating individuals with such scenarios.

Though some people prefer solo travelling for leisure, to explore new places, or for peace, a large number of people prefer to have a travel companion, who may be a spouse, children, parents, friends, relatives, colleagues, or like-minded group members. Such groups may be recommended to users [12] for enhancing their travel experience; individuals may get exposed to new activities or they may create new social connections among other groups. Hence, a tour package may be selected based on several criteria. Advertising is an important way to reach out to the targeted audiences. Many travel agencies promote themselves through various online and offline mediums; effects of such tourism advertising may include cognitive, affective, and behavioural aspects [93]. Other than the selection criteria, the organizers need to deal with potential sources which may increase stress while travelling, for example, issues with local languages, personal safety and health concerns, transport delays, unfamiliarity of customs or food [94].

In this section, various aspects of tourism such as visiting new destinations, planning one-day trips, selecting a tourism package, and group recommendations are discussed. Developing a robust system by applying different dimensions of tourism can enhance its usability.

4.1 Planning Recommendations

Travellers generally have a list of scheduled destinations to be visited and activities to be performed, however, some locations may remain unvisited due to constraints. In some cases, the tourists may not have a clear idea about the worthy places to visit. To accommodate such travellers, tour planning RSs have been developed which consider tourist preferences and recommend the appropriate places to be visited or activities to be explored.

Any RS is designed with the aim of providing the most satisfiable suggestions. However, various issues may occur and the reliability of such an RS gets highly dependent on the methods and data. To overcome common problems of CF and CB approaches, various hybrid approaches have been proposed by combining various methods. For tourism recommendation, Lucas et al. [95] proposed a hybrid approach. Authors built groups of users having similar characteristics and preferences to classify the active user and constructed a recommendation model of associative classification rules using CBA-Fuzzy algorithm [96]; the associative classification could provide more reliable recommendations on sparse data contexts whereas fuzzy rules allowed classifying a user into multiple groups. Authors validated their proposed method using personalized sightseeing planning system (PSiS) [97] which was developed to help users plan what should be done at specific places; a total of 241 POIs were selected.

There are various aspects of a tour that may include the locality, temporal details, weather forecast, and the purpose of visit. Such contexts are helpful in deciding what should be suggested to a user while planning for a tour or in real-time when the user is already on a trip. Such specifications have been exploited for domain-specific tourism recommendations. A personalized tour planner, namely eCOMPASS, was proposed to assist tourists through the public transit [98]. It was a service-oriented architecture approach which accepted queries from the users and recommended a tour. It could also examine weather forecast with the help of Yahoo! weather service. eCOMPASS allowed users to define an arbitrary start or end tour locations and scheduling lunch breaks at suitable restaurants; a multimodal route planning service was used to estimate and plan the trip accordingly. The recommended tours could be visualized using a map or a list view; the images of recommended POIs could be viewed as well. Further updatation of removing or restoring a POI was possible with eCOMPASS; details for the selected POIs could be retrieved too. Authors applied a local search heuristic, the SlackRoutes, for solving the targeted tourist trip design problem (TTDP) [99] and evaluated it for Athens, Greece and Berline, Germany metropolitan areas [98].

Various tourist attractions and geographical information of Japan railway stations were analyzed along with different contexts to generate tour plans [100]. For the experiment, details of Japan railway stations, i.e., their names, addresses, geographical coordinates, and tourism guidance offices and regional speciality shops located in Japan were collected from Navitime.co.jp website; famous attractions classified into sight-landmark, natural-park, and museum were collected from TripAdvisor.com website; cultural events and attributes such as average visiting time, restaurants' price and rating were collected from Jalan.net website whereas weather forecasting information was taken using Yahoo! API. The system generated short-term trips based on the user's preferences and the context; it also produced on-demand services in real-time. Authors tested it in Tokyo, Osaka, Kyoto, Kobe, Yokohama, Nagoya, Fukuoka, and Sapporo of Japan.

A framework, namely, filter-first, tour-second (FFTS), was proposed for producing recommendations on a multi-period personalized tour [101]. For a tourist being at a location for a given period, i.e., the number of days, the mandatory POIs were places that the tourist must visit based on his/her personal preferences, whereas the optional set of points might be optionally visited by the tourist. Such optional points, i.e., top-*N* recommendations, were filtered using item-based CF approach and user's online data; the daily tours were built with an iterated tabu search algorithm where the best solution was constructed in terms of the collected profit and the total distance travelled objectives. This experiment was conducted on datasets provided for the multi-period orienteering problem with time windows (MuPOPTW) [102] and the Foursquare dataset [103] which included four main cities of the US, i.e., New York City, Pittsburgh, San Francisco, and Boston for an eight days long trip. The points to be recommended were divided into six categories: parks, bars and nightclubs, museums and galleries, great outdoors, scenic attractions, and movie and broadway theatres. While all the mandatory points were expected to be covered, every optional point might not get covered on the trip; authors found in their experiment that an average of 73.2% of the optional points was covered [101].

4.2 Travel Package Recommendations

A travel package is selected with the aim of reducing the efforts of searching and planning the tour from scratch. Such packages largely include transportations, visiting various places, guidance during the trip, and accommodation; they are cost-effective too. A personalized travel package recommendation may be helpful to users.

A multi-agent RS, namely PersonalTour, was proposed to find suitable travel packages as per the user's preferences [104]. This approach followed the distributed AI paradigm. The knowledge bases stored recommendations to the users and their responses while evaluating the travel services were recorded. PersonalTour agent was given confidence degrees for flight, hotel, and attraction services; they were updated based on users' evaluations. This system was evaluated with 400 travel-based cases and was randomly distributed over the knowledge bases of ten agents; during the experiment, 94 travel packages were recommended to various customers. The percentage of purchasable travel packages was found to be 71.27% from the human travel agents' recommendations, whereas that of the proposed PersonalTour system was 76.59%. Authors had compared the percentages of positive rates for various travel services.

The online travel data were analyzed to identify how travel packages contained distinguish characteristics than that of the traditional items [105]. Authors studied such characteristics using a tourist-area-season topic (TAST) model where the extracted topics, conditioned on tourists and landscape features, presented travel packages and tourists. This topic model representation was utilized to propose a cocktail approach; authors generated personalized travel package recommendations using this approach. A tourist-relation-area-season topic (TRAST) model was an extension to the TAST model; it was proposed to capture latent relationships among tourists in each travel group [105]. The experiment was carried out with real-world data; 5211 tourists and 843 packages were chosen for training, whereas 1150 tourists and 908 packages were used for testing along with landscape, record, and group data. Authors compared these models to evaluate the effectiveness of the personalized travel package recommendations.

An object-oriented RS framework was proposed for recommending personalized travel package by importing the context information and creating feature-value pairs [106]. Authors proposed an object-oriented topic model for extracting conditioned topics and an object-oriented Bayesian network for inferring the co-travel probability of two travellers; the recommended list was generated using the CF approach. Evaluation of these models concluded that features having lower selection entropies had lead to higher recommendation results.

Yu et al. [107] proposed using location-based social networks for personalizing travel package; authors utilized data collected from users' social networks and derived destination preferences using the CF approach. For the experiment, 2,407,647 check-in records of 89,936 anonymous users were collected using JiePang.com. Authors considered food, venue, and entertainment types of location with 37, 17, and 17 sub-categories, respectively. They developed a heuristic search-based approach with user preference model and location popularity; the system recommended multiple POIs and the sequence of visiting them.

4.3 Group Recommendations

Tourism-related services and products are likely to be experienced in groups; a few travellers may prefer solo trips. An individual's preferences are likely to be distinct from group choices and an RS is expected to undergo a decision-making process for the overall group for tourism suggestions. Techniques of group recommendations are claimed to be strongly influenced by social choice theory [108] and not sufficiently by group dynamics studies [109]. Hence, understanding various aspects of group-based recommendations are important in tourism.

[110] adopted users' rating profile, personal interests, and specifications for the next destination and developed a hybrid approach to recommend travel destinations to groups by aggregating individual recommendations. Understanding the group preferences may help designing an appropriate tour. Nguyen and Ricci [13] proposed a chat-based group recommended interface, namely, South Tyrol Suggests for Group (STSGroup); this system recorded the discussions on group and identified user preferences; suitable directions and recommendations were given to the user. The experiment was conducted with 15 participants. Authors evaluated the

usability with system usability scale (SUS) [111] which was achieved to be 76 overall. Also, the recommendation quality was measured for the recommended POI; 80% participants indicated being excited about the chosen place.

Individuals' preferences may be presented using user-item ratings whereas their characteristics may be considered using individuals' personality traits, behavioural attitudes in the context of a group, and experiences [112]. Authors also characterized a group composition using its members' preferences, personalities, and relationships among the group members. The experimental study was conducted with 200 participants in 55 groups. Authors utilized the results and their implications and related them to seven travel-related factors, i.e., sun & chill-out, knowledge & travel, independence & history, culture & indulgence, social & sport, action & fun, and nature & recreation [112].

For enhancing the satisfaction level in the majority of the group members, an aggregation method was utilized in group recommendation using deviation [113]. Authors proposed upward levelling which recommended items with low deviations and high averages in conjunction. This approach outperformed with NDCG and diversity measures. Hence, e-tourism may be recommended to fulfil various requirements. Authors also studied how an efficient group-based RSs could be designed [114].

5 Attraction Recommender Systems

One of the main purposes of tourism is to visit various tourist attractions. The number of attractions at the specific location may vary and the time required at each spot, travelling time among the spots, available guidance, users' interest, transportation are some of the deciding factors. While planning for a tour, these attractions are taken into account and the visit is planned accordingly. However, searching through various travel blogs, websites, or other mediums to collect the required information for such places becomes a tiring task and an RS for the tourist attractions may be desired. Various RS-based attractions are discussed in this section.

5.1 Point-of-Interest Recommendations

Various locations may serve different purposes for visitors. Selection of appropriate tourist attractions is largely dependent on individuals' preferences and contexts. Many people wish to have different kinds of experiences such as exploring cultural tourism, going on adventure camps, or preferring leisure and relaxing atmosphere during a trip. Such domain-specific contexts may be exploited to recommend respective places.

For suggesting historical POIs, [115] employed a smart space approach in a mobile tourism service. A semantic network was built for the preferred POI given by the user. In the smart space-based proposed architecture, historical data were provided from different sources; a personalized structure of POIs was constructed based on the user's preferences; the ranked personalized structure was recommended to the user. Varfolomeyev et al. [116] constructed quantitative and qualitative estimates based on such information and visualized the POIs based on historical information. [117] extended the work and employed it on the history of Latgale, Latvia where the aspects of information representation for the given class of services were considered.

Another application based on smart space was developed for planning a cultural heritage trip [118]. Authors provided an ontological model with combined information on service-specific planning and recommended areas; this model also included other attributes such as description of the cultural heritage, climate time, and movement restrictions. Authors used five knowledge processors (KPs) as data sources including weather, geological information, event, geological position, and booking details collected from various modules. They also used user's positions, preferences, personal data, main attractions and planning restrictions for providing feedback on user's visit to the POI. A semantic information broker (SIB) was adopted for Smart-M3 platform [119]; review in terms of evaluation and POI ranking and time plan were included in KPs. This model was verified by various usage scenarios.

To suggest tourism POIs to a user, a content analyzer could be used to compute the relevance of each topic-of-interest (TOI) with respect to each POI. Binucci et al. [120] proposed an algorithmic engine which extracted POIs from the selected region and created a knowledge base; descriptions about the relevance of each POI with respect to the chosen TOIs were stored along with a relevance score indicating both, pertinence, i.e., the semantic relatedness and popularity of the POI as a tourist attraction. For the experiment, authors considered two geographical regions of Italian cities, Rome and Perugia whereas the three TOIs that were reviewed included religion, art, and history; the number of POIs for the chosen TOIs were 25 and 10 for Rome and Perugia, respectively. Including professional tourist guides, people having travel-related jobs, and those who had visited the city several times, a group of 12 and 8 people were recruited to score Rome and Perugia, respectively. Authors evaluated the ranking and provided percentage errors.

5.2 Museum Recommendations

Travellers have different selection criteria and interests while visiting a new place; sightseeing points, national parks, exhibitions, events, and museums are some of the most frequently visited attractions depending on the destinations and cultures. A museum can be considered as a collection of art, culture, history, or science-related artifacts which are preserved for public exhibitions. Such tourist attractions are visited to understand the importance of various aspects of the city or the culture. However, recommending a museum is a challenging task; individuals in the travel group may not share the same interest and hence, such tourist attractions may not be appreciated by everyone. In general, visitors have a limited time duration dedicated to visiting a museum and time allocation to specific artifacts should be well-organized to upgrade tourists' satisfaction; also, knowledge transfer of interesting artifacts and assistance through the museum tour are primarily desired.

Mathias et al. [121] addressed a personalized route recommendation to visit a museum. Authors identified preference criteria of visitors and their constraints such as time limit, physical barriers, or preferred museum contents to be visited; they collected artwork details such as artist's name, description, and creation date to measure intrinsic interests. Automatic text summarization and textual energy algorithm were used to rank the artwork descriptions. The personalized route was given based on visitors' interests in the given artworks and the tours were evaluated using relevance percentage measure. Authors carried out their work on the Musée de I'Orangerie, Paris having 144 artworks from 14 artists. The result improved relevance up to 49% and concluded an optimum tour duration to be two and a half hours.

For enhancing visitors' experience, a mobile-based framework was proposed by adapting user profiles, their context-sensitive information, and by exploiting museum metadata vocabularies [122]. Authors combined a semantic approach to represent the museum domain with ontologies and CF-based thesauruses. They generated a personalized tour with individuality, activity, relation, temporality, and location-based contextual information. For a dynamically adaptable tour, authors defined list and order of the artworks based on visitor's preferences, the recommended artworks, and the main artworks of the museum; the number of artworks suggested this way depended on the time duration that the visitor had wished to spend and other temporal constraints.

For a museum tour, suggesting a list of artworks to an individual [122] or their sequence to a group [123] may not be sufficient; a model was proposed to analyze the behaviour of the visitors in terms of appropriateness of the exhibited artworks [124]. Authors evaluated the audio-based contents at Chao Sam Praya National Museum at Ayutthaya; the mobile application containing 40 POIs along with their pictures, diagrams, descriptions, audio files, and videos. It was installed in 162 visitors' mobiles and more than 1500 records were collected. Authors also analyzed the time duration of audio contents of each POI to identify which POI's audio content should be reduced or the offered information should be increased. The skewness test was applied to evaluate visitors' behaviour at different POIs on different floors of the museum and the necessary improvements in the arrangement of museum exhibition were given.

Kosmopoulos and Styliaras [125] provided a detailed survey on museum service personalization; they discussed an overall workflow where an artifact closest to or being viewed by a visitor was located and the visitor's profile was analyzed; the matched contents were presented to the visitor's mobile and contextual information was collected; the exhibition reconfiguration actions were manipulated based on the curator's statistical observations. Other museum-related recommendations have been widely applied; for example, digital story crafting based on museum experience by narrative and inquiry-based learning of students [126], gaming and cognitive style-based personalizing museum visit guide [127], on-site museum guidance through relational graph [128], inquiry-based learning by means of digital storytelling [129].

Apart from POIs and museum recommendations, various attraction RSs have been developed; iTravel was proposed to provide on-tour attraction recommendations by utilizing the ratings of other tourists on their previously visited attractions [130]; CF-based friend trust relationships and geographic location contexts were combined to recommend the most interesting attractions [131]; the tourist preferences on smart tourism attraction were assessed for Hongshan Zoo of China [132]; a skyline query-based attraction RS was developed and demonstrated on the Demodulation and Encoding Heritage (DEH) system of Taiwan [133]; an attraction network was built using travel intentions for a large number of POIs to recommend travel destinations [134]; user's preferences, social relationships, location distance and popularity-based personalized tourist attractions were recommended [135]; an offline attraction RS was developed using the contextual information [136]. Events ongoing at various tourist points also have a great impact on visitors as well as local individuals; such events may be cultural activities, meetups, or celebrations. Herzog and Wörndl [137] developed spontaneous event RS for tourists and individuals who might not have specific plans to carry out; Ogundele et al. [138] integrated geographical, social, and temporal influences and considered preferences of users and their friends for recommending events with their proposed EventRec framework and extended it to employ multi-criteria decision making approach to rank events in their proposed framework, namely SoCaST* [139]. Hence, the wide range of applicability of various approaches has been utilized in the field of recommending tourist attractions.

6 Other Tourism-Based Recommender Systems

For many people, a tour is not only about the destination or accommodations; there have been many other factors which play important roles while travelling. For example, people try to capture the travel memories in pictures and convey them via social media or blogs. Such considerations may also require guidance for enhancing the experience. In this section, we summarize various recommendation aspects associated with a tour.

6.1 Food Recommendations

Food is essential for survival in our everyday life; there are various categories of food which may vary based on the ingredients, types of nutrients, the way it should be eaten, or its freshness. Various cultures have different ways of cooking and serving the food dishes. An aesthetically pleasing food presentation may have a positive impact on individuals' food consumption. Such aspects are considered while recommending food and beverages.

An experiment was carried out to examine associations of colour, music, and emotion with dish items in restaurants [140]. Authors found that in salad group restaurants, lime colour, combined with Jazz, Pop, and Soul music and peaceful and joyful emotions were frequently selected, whereas in steak group restaurant, dark-red colour, combined with Jazz and Classical music and peaceful, transcend, tender, and joyful emotions were selected. One of the results indicated that individuals valued peaceful environments for eating. On the other hand, a study on wine preferences [141] indicated that textual language was more effective for the wine professionals and organic product specialists, whereas the photographic language impacted more effectively on tourists.

While a day-to-day routine has been carried out, some people generally wish to try different varieties of food dishes whereas others choose to strictly follow the same routine. Also, the choice of food varies with time of the day, season, economic status, mood, group, and many other aspects. The food may be prepared and sold in restaurants, hotels, cafeteria, home-made, local shops, on streets, or even food trucks. These induce different ways to order food; identifying the most preferable dish according to the context becomes very difficult. Hence, food recommendation must match up to a vast range of different expectations in real-time. Considering the moving behaviour of food trucks in various large-scale events such as concerts or festivals, [142] pointed out the issue of selecting a food truck from the available variety of possible cuisines and food dishes. The experiment was carried out with 15 objective questions about food truck preferences and habits and 6 objective questions about the participant's profile. Authors applied six multi-label transformation strategies on data collected from 407 participants; results obtained using ten-fold cross-validation were compared with random forest algorithm. Our survey is compared with [19] in Table 1.

6.2 Photography Recommendations

Photography has been considered as an art; we capture the moments and convey various messages through pictures. It may be a part of our everyday routine; we try to click pictures of ourselves, friends, nature, buildings, or any subject that may interest us. Such pictures may be assessed by means of its aesthetic properties or photo quality, however, every individual may not be able to take a picture in the best way; different people would look at the same object differently and the photograph would have different representations. The general human tendency would wish to look graceful in the pictures and hence, an RS may be helpful in deciding the way a picture may be taken.

Aesthetics is a branch of philosophy; it is the way in which the beauty of the photographs can be characterized and expressed [143]. Majority of professional photographers consider such aesthetic properties. Zhang et al. [144] collected such professional photos from photo.net website to create a reference dataset. Human poses were estimated from this dataset using methods given in [145]. To obtain an aesthetic spatial composition representation for portrait photography, authors used attention composition and geometry composition features. A hierarchical k-means clustering method was applied on the attention composition of a query photo to find the nearest-neighbours; a matching process with reference photos was carried out. To measure the scene structure, geometry composition features were used and the reference photographs were selected using the rule of thirds and the golden ratio [146]. From the editorial and fashion fields, the dataset consisted of 232 photographs whereas the proposed approach was tested on 50 images. The effectiveness of the recommended photos was evaluated in terms of pose and position with the help of 10 participants and a satisfaction rate of 57.6% was achieved.

A photo-taking app was developed for reminding to take pictures of attractive scenes based on the user's context [147]. This approach aimed at enhancing the user's photo collection at a tourist site. Using the geographical location, the app analyzed the scene and extracted features; similarity-based searching was carried out according to the context. The dataset included pictures of popular tourist spots of Japan, China, and Hong Kong; these were randomly collected geotagged pictures from the Internet. Gist descriptor was used [148] for image content similarity matching.

Here, photographs within a distance of 2km from the user's location were considered and the sample photographs were displayed for suggestion.

For getting the best look in pictures, an important aspect is how one should pose while taking a selfie, i.e., an image having a self-portrait. Selfie is a popular social phenomenon for expressing oneself, getting attention, or becoming a part of a community [149]; a large number of selfies are being posted on social networking websites every day. People generally have a tendency of repeatedly taking selfies with the hope of getting an even better picture than the previous one. Instead of using post-processing ways to embellish a photograph, Hsieh and Yeh [150] proposed an RS to suggest a good look in terms of a head-pose before clicking a picture. For this purpose, authors collected two face image datasets, namely, the Facebook beauty dataset [151] and the labelled faces in the wild (LFW) dataset [152]. While the former dataset contained 6785 selfie images of ordinary people, mainly of Taiwanese women, the latter dataset included 12973 face images, majorly including celebrities; an important difference in these two datasets was the face pose of the subject rather than the attractiveness [150], however, because several guidelines have been commonly followed while posing, selfies taken in aesthetically correct ways would likely be having common patterns. Authors determine head-poses, i.e., pitch, roll, and yaw and extracted 69 facial landmarks using IntraFace [153] and Fast-AAM [154]. Isolated facial features or the spatial relationships between facial features could represent the facial beauty [155]; authors presented a pattern by lines connecting two facial landmarks. They also defined 45 physiognomic line patterns of horizontal and vertical classes; the line patterns were normalized by face width and height, respectively, and quantized into M bins [156] for converting into items. Also, the frequent and distinctive patterns were identified and association rules were mined to recommend head-pose. This experiment was tested using 50 selfies; instructions for horizontal direction, i.e., turn head left, stay static, turn head right, and for vertical direction, i.e., tilt head up, stay static, tilt head down, were suggested. The interrater reliability was assessed using the Fleiss' kappa and the pairwise Cohen's kappa metrics.

6.3 Outfits Recommendations

Apparel has been a largely explored feature for almost all human societies. Variations have been largely adopted in clothing styles as per cultures, occasion, gender differentiation, individualism, and social status [157]. What should be worn for during a specific occasion may be a challenging task for many. For example, a corporate dinner may expect a relatively formal and elegant dress. The same applies while going out on a tour; factors such as locality, travel type, weather condition are preferably taken into account. Thus, an outfits RS may be desired even while travelling.

A commonsense reasoning-based novel recommendation technique was introduced [158]. This scenario-oriented recommendation was intended to help users map daily scenarios with appropriate product attributes such as outfits. The clothes style was determined using brands, types, and materials of the attire and occasion-related texts given by the users. On the other hand, such styles were represented using six dimensions, viz. luxurious, formal, funky, elegant, trendy, and sporty [158]. The default style values were derived for the clothing items; the occasions were identified for a personalized and social recommendation. This pilot study was conducted with 7 subjects, 87 clothing items in 82 types and 21 brands.

Selection of clothing items and their colour combinations, especially while travelling was studied to identify the correlation between clothing and locations from social photos [159]. Authors proposed location-oriented clothing recommendations using multilabel convolutional neural network (mCNN) and combined it with support vector machine (SVM) to derive the correlations. Some of the previous works had demonstrated a strong correlation between location and fashionability, however, discrepants such as temperature, weather were ignored [160, 161]. Zhanget al. [159] observed photo data from Mafengwo.com and Chanyouji.com websites and determined location attributes which had influenced outfits. Their experiment was carried out on Paper Doll [162], Fashionista [163], Clothing Co-Parsing [164], Colorful-Fashion [165], and Journey Outfit datasets and generic, attraction colour, and clothing colour visual features; the proposed approach outperformed with 10.52–16.38% mean average precision (mAP) on recognition of the clothing items and 9.59–29.41% mAP on suitability of outfits for the travel destinations.

6.4 Transportation Recommendations

Travelling from one place to another requires a mode of transportation such as taxi, bus, train, or other ways. These transportations have been primarily used by the majority of the people on a daily basis. An extensive number of such facilities give rise to transportation RSs for locating a vacant taxi, shorter travel time, and economical journey.

Many people prefer to travel by taxi on a routine basis or occasionally and locating a vacant taxi may become a tedious task especially during the rush hours. To resolve this problem, Yuan et al. [166] developed an RS which could learn mobility patterns of passengers as well as picking-up/dropping-off behaviour of taxi drivers using GPS trajectories. Such a system was designed to be useful to the taxi drivers by providing potential locations and routes on which they were likely to pick up passengers quickly. On the other hand, people look for a taxi might get notifications of nearby locations so as to possibly get a vacant taxi for transportation. Yuan et al. [166] proposed a taxi recommender where the range query was performed according to the taxi location and a set of potential parking places were retrieved and ranked to generate top-*N* parking places recommendation for the driver in real-time. Similarly, the passenger recommender performed the range query to obtain a walking distance nearby the user and neighbouring parking places along with the road segments were given to the user; he/she might choose to rank top-*N* road segments based on the probability of finding a vacant taxi or the average waiting time. To conduct this experiment, authors evaluated the road network of Beijing; the GPS trajectory was recorded by over 12000 taxis within 110 days in the year 2010. It was shown that the proposed approach outperformed the k-nearest neighbour (kNN)-based method in terms of precision and recall.

A framework, named TourSense, was proposed to identify tourist and analysis of preferences using transport data on city-scale such as bus, subway [167]. The learnt analytics of tourist preferences were used to predict the next tour. This experiment was conducted on 462 million trips carried out by 5.1 million travellers. The results achieved 0.8549 and 0.7154 macro and micro F1 scores, respectively. Hence, transportation-based tourist identification could be effectively utilized.

6.5 Safety Recommendations

While travelling, one of the most crucial concern is the safety of an individual. The security aspects are concerned with individual's health, their welfare during the journey, and protection against the possible risks; various agencies provide travelling insurance policies which may cover delays in transportation, especially flights, cancellations, loss of baggage, emergency medical evacuation, and other accidental or sickness-related medical expenses. The travelling risks also dominate negative social effects on the host society such as increased gambling activities, racial tension, or even loss of cultural pride [1]. Hence, identification of potential risk factors and the development of prevention techniques are desirable in tourism RSs.

While travelling abroad, tourists concern to identify the perceived travel risks, for example, terrorism. Rittichainuwat and Chakraborty [168] studied the implications of terror attack threats and its impacts on Thailand's hospitality; authors mentioned that such incidents could directly affect the tourism industry. They found in their survey that individuals had not cancelled travelling because of the fear of perceived risks, however, tourists had preferred travelling to destinations which had seemed to be comparatively more secure. Authors also analyzed concerns of tourists visiting for the first time and those repeating their trips. Other aspects apart from terrorism under the perceived risks were identified to be increased travel expenses, lack of novelty seeking, diseases such as SARS or bird flu, deterioration of tourist attractions, and travel inconvenience [168]. Authors significantly confirmed that media coverage could generate unnecessary fears on the extent of perceived risks [169].

Public transports can be largely found in a majority of the cities; these are group travel systems, mainly available for the general public. The mobility provided with public transports can help create economic opportunities in the city. Private transports are likely to be expensive as compared to the public modes of transportation. However, personal security is a prime concern while travelling using public transits; Beecroft and Pangbourne [170] studied the role of traveller information for the same. Though the security of an individual may be related to crime and anti-social actions, authors also claimed that fear of potential crime was affected by an individual's conviction on travelling. They performed the SWOT analysis, i.e., strengths, weaknesses, opportunities, and threats, along with scenario planning and expert interviews to derive significance of travellers' information in providing personal security.

Travelling on longer routes may consume a lot of time and hence, people generally prefer to travel by flights. An important aspect of travelling may be having an economical trip in general. However, facilities such as seating space may be limited in economical cabin environment; many travellers may experience discomfort in the long haul flights. Hence, the stress levels increased for in-flight passengers need to be reduced for a smooth flight journey. Liu et al. [171] targeted the necessity of a comforting environment for the in-flight experience and introduced the requirement to accommodate passengers with relaxing music. For this purpose, authors considered the heart rate; bradycardia and tachycardia are the states of having lower or higher heart rate than the normal one, respectively [172]. Following the research analysis that stress could be indicated using the heart rate, authors collected music metadata such as title, artist, album, track number, tempo, and other details along with passengers' demographic information and music preferences [171]; using the adaptive inference component in the hybrid RS, authors recommended personalized music which could be applied to help user brings his/her heart rate within the normal range. They simulated the experiment for long haul flight from Europe to Asia; the self-reported measures indicated reduced stress level and corresponding heart rate.

6.6 Weather-Based Recommendations

Though majority of the tourism RSs focus on accommodations, food, travelling, social, time-oriented and other geographical features, limited work has been carried out by considering weather-based contexts for recommending POIs to the users. Travellers prefer to carefully select the weather conditions to be suitable for their trip. For example, visiting a hilly area during monsoon may not be preferable due to the heavy risk of landsliding or, hill stations are likely to be visited by many travellers during summer. The seasonality factors may cause loss of profits, inefficiency of resources, and other difficulties to the managing authorities. Hence, weather-based recommendations demand more attention in tourism [173, 174].

Seasonality of the tourist destinations may be considered as a manipulating factor of policy-making decisions for the trip and respective locations included in the trip. A detailed analysis was carried out on the implications of seasonality in tourism [175]; authors focused on the seasonality factors on weekly, monthly, and yearly basis with respect to the tourism demand. They introduced the usage of entropy and relative redundancy measures instead of using traditional Gini coefficient. A case study was conducted on the arrivals to and departures from the Balearic Islands by means of air transports; the data was collected from the Spanish airport manager.

To understand the impact of weather on the users' decision for certain POIs, [11] expanded Rank-GeoFM POI recommender algorithm. Authors included other features related to weather condition such as temperature, sky coverage by clouds, humidity, wind speed, visibility, pressure, intensity of precipitation, and moonphase. They experimented with 3 million check-ins made by 50000 users from the Foursquare dataset [176]. They analyzed various categories of POIs and features regarding the city contexts. The performance improvement measured using NDCG indicated a significant impact of weather context on the user's check-in behaviour in various cities.

7 Concluding Remarks

The objective of our survey is to understand the significance of recommendations in travel-based applications. Travelling has been explored by almost everyone at some point in their life and the experience may be useful to others. Many people express it to friends, relatives, and others by word-of-mouth, sharing pictures on social networking sites, writing travel blogs, and even by rating and reviewing respective destinations on different websites. Reviews of travellers are useful to many others for planning their trip; they are also important for tour-planning authorities and hosting places to build a better tourism experience to attract a large number of visitors. The tourism industry also plays a vital role in the economy of the states and hence, government bodies largely support such activities. We have described various aspects of e-tourism, products, and services and categorized them into broad modules such as hotel, restaurant, tourism planning, and tourist attraction. We have discussed various features affecting the selection of a module; an overview of existing travel-related service RSs is provided for the same. A traveller may have diverse expectations with the journey, hence, we have extended our survey to cover recommendations in potential fields related to tourism. We have reviewed RSs on food and beverages, photography, and outfits; other important concerns such as security while travelling, transportation, and climate-based tourism recommendations have also been explored in this article.

A travel RS necessitates knowledge of numerous factors; insufficient information may lead to poor recommendations or high dissatisfaction in users. We have discussed datasets adopted from various websites such as TripAdvisor.com or Foursquare.com having reviews, ratings, check-ins or other details. Due to varied reviewing tendencies of people, identification of unbiased data may be a major concern. Also, the preferences for travelling periods, for example, visiting hill stations in summer, or taking international tours during long vacations, may get influenced during peak periods; a large number of tourist places are likely to face heavy congestion and the overall experience may be affected by specific contexts. Another important aspect of tourism is adaptability. Recommendation of travel packages to physically and/or mentally challenged people, as well as the aged people, may be considered as an open issue for travel RSs. Development of a robust travel-based RS would require adaptation of such diverse aspects. E-tourism may be associated with other domains such as e-shopping, e-learning, or e-commerce for magnifying its potential applications and the future directives may encourage interested researchers to enhance the acquaintance with tourism RSs.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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