A Survey on Personalized Itinerary Recommendation: From Optimisation to Deep Learning

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Abstract

The tourism industry is a significant contributor to the global economy, responsible for generating nearly 10% of the world's GDP and employing around 9% of the global workforce. A crucial aspect of this industry is personalised itinerary recommendation, where visitors' preferences and constraints are taken into account to create customised travel plans. This task involves selecting the best points of interests (POIs) for visitors in various cities and then schedule these POIs as an itinerary considering numerous constraints. However, due to the varied ways in which researchers have defined the itinerary recommendations, it can be challenging for new researchers to locate up-to-date literature on the topic. As a result, this paper aims to review existing research in this area and provide a taxonomy of the works based on problem formulations, proposed techniques, constraints, and features used. We divide the study into two directions: user satisfaction and provider satisfaction, where user satisfaction is derived non–personalised and personalised POI/ Itinerary recommendations. We also discuss the data sources, techniques ranging from optimization approaches to deep learning and evaluation methodologies commonly used in this field. Finally, we highlight the importance of personalised itinerary recommendation and identify areas for future research to address the current challenges.

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Personalised Interest, Provider Satisfaction, Deep Learning

1. Introduction

Tourism is an important leisure activity that generates significant economical impacts, contributing to a staggering revenue of US $7.2 trillion and accounting for 284 million jobs annually [1]. A key task in tourism is planning a personalized itinerary for visitors, which is challenging due to elements of both a recommendation problem i.e., selecting appropriate POIs and an optimisation problem i.e., scheduling visits to these POIs as a connected itinerary with various temporal and spatial constraints. Furthermore, visitors have personalized interest preferences that are potentially dynamic and depend on spatial and temporal factors, such as having a limited time budget to complete the entire tour and starting and ending the tour plan in a particular location (e.g., home, airport, or hotel).

While tourists can refer to online tour guides and use the services of travel agencies, these sources typically suggest generic POIs or standard tours that do not align with the tourist's interest preferences or various trip constraints. To address these challenges, researchers have developed solutions for tour itinerary recommendation problems using a variety of data sources and techniques ranging from optimization approaches to deep learning techniques. In the Operational Research community, tour recommendation is formulated as an optimization problem where the primary goal is to plan an optimal path to maximize global metrics such as POI popularity and static users' preferences. However, the users' dynamic preferences are not considered, which depend on complex temporal and spatial constraints that do not correlate linearly. The popularity of location–based social activities (geo-tagged social media) and widespread use of smartphones have led to an increased focus on data–driven methods, for improving tour recommendations that take into account users' preferences and various constraints. This paper describes different existing data-driven tour recommendation models, problem variations, proposed solutions, and applied evaluation metrics in detail.

Travel itinerary recommendation is closely involved with next location recommendation [2, 3, 4, 5, 6], top-k location recommendation [7, 8, 9, 10], and package/region recommendation [11, 12, 13]. Recently, deep learning techniques [14, 15, 16, 17, 18] have attracted significant attention due to their good performance and ability to handle multiple features. The primary aim of next location recommendation and prediction is to select the next suitable location based on a user's previous preference patterns. Similarly, TOP-k or region/package recommendation aims to recommend POIs as a ranked list or in a group. Ranked list recommendations provide personalized suggestions for POIs in a user-specific order, taking into account individual preferences. On the other hand, group-based recommendations offer a curated selection of POIs that are best enjoyed together, making them ideal for trip planning. In contrast, the main aim of tour itinerary recommendation is to select multiple locations as a sequence and form user trajectories, thus involving elements of an optimization task and recommendation task. Therefore, tour itinerary recommendation has the additional challenges of connecting POIs to POIs where spatiotemporal constraints and a limited time budget factor change users interest.

Tour itinerary recommendation is closely associated with the travel path design problem, commonly investigated in operational research. Different survey papers [19, 20] explore different problem formulations, algorithmic structures, and complexity analyses. Numerous tour recommendation research works define these problems based on the Orienteering problem and its variants [21, 22]. The research work [23] describes artificial intelligence models used as different interface types, system functionalities, and recommendation techniques for itinerary recommendation. Another survey study [24] discussed works that make recommendations using location-based social networks. Lim et al. [20] described a tour recommendation research survey focusing on various aspects of users' individual and group recommendations. While these works present engaging surveys of related work in itinerary recommendation research, they do not cover the latest developments in itinerary recommendation. Some of the existing surveys focused on feature-based classifications. For example, Zhao et al. [25] presented a study of POI recommendation considering four influential factors, i.e., geographical information, social relationship, temporal influence and content indications. They also categorised methodology based on the focused model and joint model, but did not focus on model techniques in detail. Werneck et al. [26] described a systematic mapping of POI recommendation-related published papers in prestigious journals and conferences (e.g., RecSys, VLDB, SIGIR, WWW, TKDE, etc.) for selected years (2017, 2018, and 2019). This survey does not cover recent years' publications, especially from 2020 to 2022. Chaudhari et al. [27] highlight various factors associated with travelling, including hotels, restaurants, tourism packages, planning and attractions. They categorized travel-based recommendation systems and multiple frameworks, even did not discuss technical contributions or advanced algorithms. Da et al. [28] proposed a recommendation system based on deep learning methods-based survey for item recommendation that did not discuss POI recommendation. Recently, Sarkar et al. [29] presented tourism recommendation systems (TRS) considering environments, geo-coordinates and user preferences. Therefore, our survey paper is different than these survey papers due to several reasons. First, we present tour-related recommendations considering user and provider aspects, whereas existing works did not consider these two influences. Most of the survey papers considered only users' preferences and relevant constraints. Secondly, we considered three categories (personalised, non-personalised and fair) of recommendations-based studies that were not covered by the existing survey. Third, we analyse current technology-based recommendation systems, especially deep learning-based POI and itinerary recommendations. Fourth, we also present fair recommendation techniques that cover user interest and provider satisfaction together. Fifth, a set of advanced future research directions has been suggested for future researchers. Finally, we can say this survey paper will help to provide a comprehensive and up-to-date overview of POI/ literary recommendation, consolidate existing knowledge, and make the research more accessible to the researcher in this field.

This survey paper aims to address these issues and summarise our research contributions as follows.

- We discuss recent works on itinerary recommendation that use deep learning techniques as well as those that consider the aspect of fairness from the perspective of the user and provider.
- To provide a better broad overview of research on itinerary recommendation, we pro-

pose a taxonomy (Figure 1) that depicts the research field of tour itinerary recommendations, which is separated into two research directions: user satisfaction and provider satisfaction.

- We further divide the user satisfaction into two sub–categories: non–personalised and personalised. In the non–personalised recommendation context, all users receive the same recommendation; by contrast, personalised recommendation users receive an individual recommendation based on their preferences. We also consider a provider satisfaction-based study that all providers in the system achieve satisfaction based on the utilisation of their resources.

- These three categories of non–personalised, personalised and provider satisfaction research cover the sub–areas of operations research, recommendations and fairness have been discussed in this paper.

- Furthermore, we suggest some interesting research directions that future researchers can explore.

Here, we elaborate on different categories of itinerary recommendation research that have been covered in our proposed taxonomy (Figure 1). Firstly, we divide our literature studied into two classes: user satisfaction and provider satisfaction. User satisfaction mainly comprises personalised and non–personalized recommendations. Non–personalised satisfaction covers operations research and recommendations, while operations research relates to orienteering problems and itinerary recommendations. Then, personalized recommendation is introduced, which tailors recommendations to individual users' preferences. Within this category, we provide an in-depth discussion of existing works related to itineraries and POIs recommendations, covering itinerary recommendations, top-k, next, and package recommendations. After that, provider fairness is addressed, which concerns providers' satisfaction with their resource utilization. This aspect relates to fairness and fair recommendations; here, fairness only considers provider happiness without user satisfaction, while fair recommendations maintain both user and provider satisfaction. We first describe different task–based

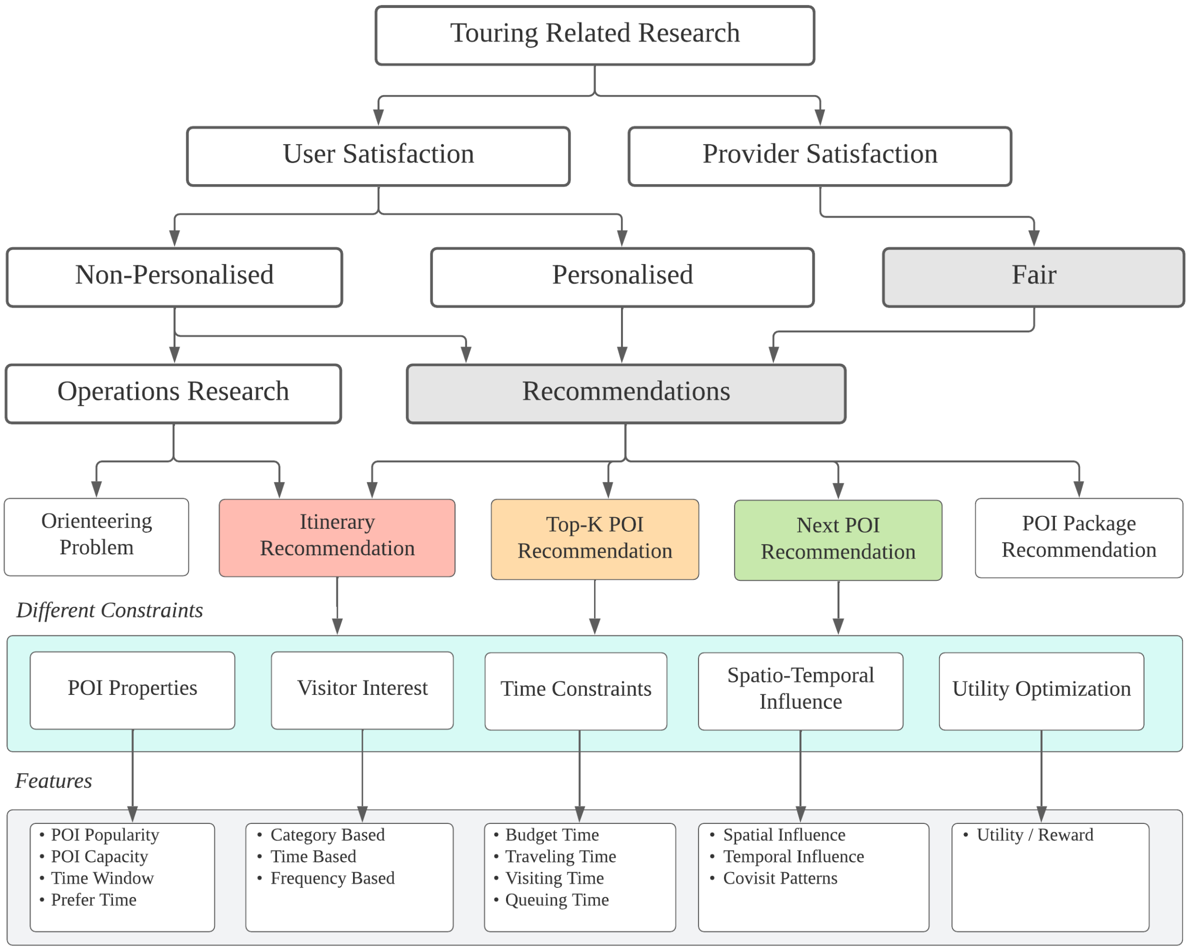

Figure 1: Taxonomy of tourism–related research works. Coloured blocks indicate the area of research interest.

models that consider non–personalised and personalised user interests. Furthermore, we review various deep learning models in the POI/ itinerary recommendation context. Finally, we discuss fairness issues based model in POI recommendations.

The remaining sections of this paper are organised as follows. Section 2 describes the details of data collection sources. Section 3 illustrates general user satisfaction–based recommendations, including operational research works and general recommendation systems. Section 4 describes personalised user satisfaction-related recommendation problems and solutions in detail. We present deep learning–based itinerary and POI recommendation models in Section 5. Section 6 discusses the existing work on fairness in recommendation models.

Then, Section 7 presents the model evaluation metrics. We highlight the significance of itinerary recommendation research and explore the potential future directions of this field in Section 9. Finally, Section 8 concludes the paper by summarising the main contributions of itinerary recommendation research along with the key findings.

2. Data Retrieval and Sources for Tourism Research

The initial step of most tour recommendation research is to retrieve a data source that reflects users' real-life tour history, which is then used to evaluate the performance of the proposed tour recommendation models. We discuss three popular data sources for these works, namely: geo-tagged photos, location-based social networks and GPS trajectories.

Geo-tagged Social Media: Geo-tagged social media, such as geo-located photos, are frequently used for many tours and POI recommendation works [30, 31, 32, 33]. These works typically retrieve geo-tagged photos, map these photos to POIs to obtain POI visits, then construct user trajectories based on these POI visits. User interest preferences are then derived from the categories of POI visits. These user trajectories are then used to train and evaluate itinerary recommendation and planning algorithms. Apart from geo-tagged photos, this approach can also be easily extended to other forms of geo-tagged social media, such as tweets [34].

Location-based Social Networks: Location based Social Networks (LBSNs), e.g., Foursquare, Gowalla, are another source of trajectory data where users explicitly check-in to specific locations. These check-in locations are divided into different categories, e.g., restaurants, parks, entertainment, etc., which can be used to model user interest preferences. These types of data sources are also commonly used in various tour recommendation and path planning works [35, 36, 17, 37, 10, 8].

GPS-based Data: With the widespread use of smartphones and GPS-enabled devices, GPS-based data is becoming an increasingly popular data source for tour recommendation and planning problems [38, 39]. Unlike geo-tagged social media and LBSN data, GPS-based data are significantly more precise and can capture fine-grained user movement patterns that are not based solely on visits to specific POIs or locations. However, GPS-based data potentially suffer from user privacy issues and are thus less readily available than geo-tagged social media and LBSN data.

3. General Non–personalised User Recommendation

General satisfaction–related problems can be broadly divided into (i) operational research and (ii) recommendations. This section describes operational research and the general recommendation problem in detail.

3.1. Operational Research

Researchers have proposed different adaptations of the path–generating problems through a set of nodes. Among them, a frequently studied orienteering problem (OP) involves creating a path across a set of nodes and aiming to maximise the total score within budget time. Existing operational research works do not consider personalised user interests; however, these personalised interests play a significant role in individual satisfaction. In this case, all users receive the same itinerary recommendation when the same starting/ending location and budget time are given as input.

Table 1 shows a brief overview of different research works on tour itinerary recommendations for general user interest.

3.1.1. Orienteering Problem

An OP is a routing problem that generates a path through a set of nodes and maximises the score within the budget limit. The operational research community has utilised the OP for tour recommendations. The general OP is about a runner needing to go to different locations, each associated with a certain number of activity points, and the aim is to collect as many rewards as possible within a budget time. Tour recommendations generally focus on the individual city–based recommendations. Here, each city has a set of visiting spots or POIs P, where the total number of POIs $|P| = N$. Visitors wish to visit the city within their budget time B and have a preferred starting location p_1 and ending location p_N. The

Table 1: Existing user satisfaction–based work on tour recommendation.

Users Mode	Existing Works	Popularity	General Interest	Determines Interest	Constructs Itinerary	Considers Time	Transport Traffic
Single	Gionis et al. [40]	✓	Partly	✗	✓	✓	✗
	Bolzoni et al. [41]	✗	✓	✗	✓	✓	✗
	Brilhante et al. [31]	✓	✓	✓	✓	✓	✗
	Yahi et al. [42]	✓	✓	✗	✓	✗	✗
	Majid et al. [32]	Partly	✓	✓	✓	✓	✗
	Chen et al. [43]	✓	✓	✓	✓	✓	✓
	Gavalas et al. [44]	Partly	✓	✗	✓	✓	✓
	Zhang et al. [45]	✓	✓	✓	✓	✓	✓
	Zhang et al. [46]	✓	✓	✓	✓	✓	✓
	Lim et al. [47]	✓	✓	✓	✓	✓	✗
	Lim et al. [48]	✓	✓	✓	✓	✓	✗
	Halder et al. [49]	✓	✓	✓	✓	✓	✗
	Quercia et al.[50]	✗	✗	✗	✓	✗	✗
	Galbrun et al. [51]	✗	✗	✗	✓	Partly	✗
	Yu et al. [52]	✓	✓	✓	✓	✓	✗
	Jiang et al. [53]	✓	✓	✓	✓	✓	✗
	Chen et al. [54]	✓	✓	✓	✓	✗	✗
Group	Anagnostopoulos et al. [55]	✓	✓	✓	✓	✓	✗
	Basu et al. [56]	✗	✓	Partly	✗	✗	✗
	Garcia et al. [57]	✓	✓	Partly	✓	✓	✗
	Chen et al. [58]	✓	✓	✓	✓	✓	✗

main goal of the OP is to select a tour itinerary that maximises a specific reward score within the budget time. The score is a user–defined function that users can define in various ways. We can define the recommended itinerary as $I = (p_1, p_2, \cdots, p_N)$ and further define the following:

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} Path(p_i, p_j) \times Score(p_i), \tag{1}$$

where

$$Path(p_i, p_j) = \begin{cases} 1 & \text{if user visits POI } p_i \text{ and subsequently travels to } p_j \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

and, $Score(p_i)$ is the user satisfaction score of POI p_i.

This is subject to:

$$\sum_{j=2}^{N} Path(p_1, p_j) = \sum_{i=1}^{N-1} Path(p_i, p_N) = 1 \tag{3}$$

$$\sum_{i=1}^{N-1} Path(p_i, p_l) = \sum_{j=2}^{N} Path(p_l, p_j) \leq 1, \forall l = 2, 3, \cdots, N-1 \tag{4}$$

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} Time(p_i, p_j) \times Path(p_i, p_j) \leq B \tag{5}$$

The OP maximises the certain score in Equation 1 by allocating POIs in the itinerary recommendation. The score is generally based on POI popularity, user interest or both. Equation 3 stipulated that the start and end locations are specific and start from p_1 and end at POI p_N. The recommended tour path is an entire path, and there are no repeated POIs (as ensured by Equation 4). The recommended tour time will be less than the budget time according to Equation 5, where $Time(p_i, p_j)$ represents the total time from POI p_i to p_j, including travelling time, visiting time and queuing time.

3.1.2. Variants of the Orienteering Problem

Recently, researchers are focusing on various variants of the orienteering problem. Xiaoling et al. [59] integrated A* algorithm into dynamic traffic model path planning for designing scenic routes by combining the cellular transport model (CTM) model with the Greenshield model. Xu et al. [60] addressed an urgency-based personalised route planning model by leveraging historical tourism data and road network information to utilise urgency values to offer travel routes that align with user interests and urgency. Gao et al. [61] addressed the issue of route planning in city-scale networks, considering varying travel times and utilities over time, a factor often overlooked. The authors suggest a two-phase framework for efficient route planning that creates an edge table for managing time-dependent data and sequentially generates routes. Cost-effectiveness, and superior utility-maximizing performance while minimizing computation time. The COVID-19 pandemic led to a rise in nature-based tourism, but this has caused environmental issues due to motorhome and campervan use. Garcia et al. [62] proposed a system that collects trip data and user preferences, connecting to a recommender system for tailored POI recommendations. Itineraries can be created to reduce carbon footprint and a novel solution using Large Language Models is presented to address the cold-start problem in POI recommendation. Vathis et al. [63] utilised multi-level clustering and dynamic programming to define and solve the Vacation Planning Problem (VPP) for tourists by incorporating geographical constraints. Cao et al. [64] proposed an enhanced genetic algorithm (IGA) to optimize travel routes, enabling efficient visitation of multiple tourist destinations. Zhong et al. [65] addressed the challenge of personalized multi-day urban trip planning considering the time windows and transportation mode recommendations. Chalkiadakis et al. [66] introduce an innovative hybrid recommender system for tourism that utilizes a Bayesian preferences elicitation component based on user ratings of generic images representing points of interest to construct user profiles in combination with unique content-based recommendations.

3.1.3. Itinerary Construction Problems

As noted above, many existing works on itinerary recommendation [30, 67, 68] are based on the OP [69, 21] whose main aim is to maximise a global reward point within a user–defined time budget. Location popularity is generally utilised as a global utility in theme park [70, 71] and city [72, 68] itinerary recommendation. Many significant tourism–related works utilise geo–tagged photos [73, 30] to identify popular POIs and subsequently analyse tourist interest. While these recommendations are interesting, they do not consider visitors' personalised interest preferences. Yoon et al. [74] introduced an efficient and balanced intelligent tour recommendation model using global positioning system (GPS) itineraries. Lim et al. [20] presented a detailed description of a social media data–based tour recommendation model and itinerary planning models based on a survey study.

Choudhury et al. [67] employed geo-tagged photos to extract tourist trajectories and proposed an itinerary mining problem based on the orienteering framework. Their approach aims to maximize POI popularity while keeping the itinerary's total transiting and visiting time within a pre-determined budget. To achieve this, the proposed model calculates the median transit time and the seventy-fifth percentile staying time-based on all visitors' transit and visiting time, respectively. To solve the itinerary mining problem, the authors used a recursive greedy technique [75]. This approach estimates a center POI of the itinerary, incorporates the associated popularity reward, and recursively adds POIs while considering the remaining budget time.

Gionis et al. [40] introduced a modified version of the OP that incorporates starting and ending POI constraints and a specific time or distance as a budget value. In contrast to the original OP, their model uses POI categories to recommend POIs based on a predefined travel order that covers all categories, such as $Cafe \rightsquigarrow Parks \rightsquigarrow Restaurants \rightsquigarrow Shopping \rightsquigarrow Museum \rightsquigarrow Beach$. To accommodate flexibility in the recommended itinerary, the authors proposed three variations of the OP: partial ordering, subset grouping, and skipping. Partial ordering follows the POI category order to some extent, such as $Cafe \rightsquigarrow Parks$ and $Shopping \rightsquigarrow Museum$ are partial orders of the above sequence. Subset grouping allows visitors to travel to any one of the subsets of POI categories, such as a recommendation for $Cafe$ or $Restaurants \rightsquigarrow Shopping$ or $Museum$ or $Beach$ or $Park$ will be subset grouping in all POI categories sequence. Skipping allows for skipping one or more POIs to construct a POI itinerary from the POI category order. The authors employed two schemes to evaluate the recommended itineraries: the satisfaction function and nearby POIs. The satisfaction function measures personal satisfaction based on a universal measure, such as POI popularity, and the number of surrounding POIs that can be visited as part of the tour path. Dynamic programming technique has been used to solve these problems.

3.2. General Recommendation Problems

Recommendation-related problems have received significant research attention and can be further classified into several categories. The first category focuses on recommending a popular set of POIs as a package without considering users' personalized interest preferences. The second category focuses on recommending the top-k POIs based on spatiotemporal features. The last category concerns itinerary recommendations that enable users to travel the entire path within their budget and time constraints. The following subsections describe existing work in detail.

3.2.1. POI Recommendations

The next POI recommendation has a significant impact on both users and POI owners. However, it is also challenging due to the complexity of tour patterns and the rich contexts of sparse check-in data[1]. The *LORE* model [76] incorporated geographical and social influences to design a suitable recommendation technique based on a check-in dataset. Similarly, a convolutional Long Short-Term Memory (LSTM) network captured temporal and spatial dependencies as part of a model that ignored user interests [77]. Chang et al. [78] introduced *DeepPIM*, a deep neural POI imputation model that automatically utilized visual, textual, and temporal data. The context-aware hierarchical model CAPE [36] used user check-in sequences and POI text content for POI recommendations but did not consider users' personalized interest preferences. Zhou et al. [35] introduced a common framework to incorporate different types of contextual information for POI recommendations. The time-aware POI recommendation model *STELLAR* [79] was developed to demonstrate the effects of three-slice time interval successive check-ins. Zhang et al. [80] proposed a probabilistic model that considered different time slots in a day and the day of the week, including the effects of weekends. Notably, these models are generic and unable to distinguish personalized interests. Debnath et al. [81] presented a time–aware and preference-aware route recommendation system.

In addition, some works [82, 83] have applied convolutional neural networks and multilayer perceptrons in POI recommendation. These models used POI images to find latent vectors but could not differentiate between nearest and more distant POIs. Huang et al. [10] proposed an attention-based spatiotemporal Long Short-Term Memory (*ATST-LSTM*) network for the next POI recommendation. However, this model did not consider user interests,

[1]Sparse check-in data means there aren't many records of people checking in or visiting different places.

as the authors used user vectors that could not capture personalized interests appropriately. Moreover, Zhou et al. [9] introduced a generative discriminator-based POI recommendation model to maximize the learned probability distributions and optimize differences between true check-ins and recommended POIs. These single-task learning models recommend only the next POIs to the user based on different features. Pang et al. [84] introduced a hierarchical attention mechanism for POI recommendation. Shu et al. [85] introduced a method to predict and estimate queuing time-based on positioning data. However, none of the models discussed above can recommend top-k POIs or predict queuing time in a way that incorporates spatiotemporal features, average queuing time, and user interests.

Top–k POI recommendation is a unique variation of POI recommendation in which the number of next POIs is k. In these cases, all top–k POI recommendations are ranked based on the next–k POI recommendations. Several top–k POI recommendation works have been developed based on collaborative filtering (*CF*) or matrix factorisation approaches. The primary goal of these models is to create a ranked list based on specific scores and recommend the top–k POIs to tourists. User–based CF (*UBCF*) for itineraries [86] was utilised to recommend top–k POIs considering the social influence and spatial influence. Kotiloglu et al. [87] proposed a "Filter–First, Tour–Second" framework; here, the first phase finds the top–k optional set of POIs using *CF* [88], which are added to mandatory visited POIs to create a possible itinerary recommendation. An iterative heuristic approximation (*IHA*) [45] method was also proposed, which creates a set of attractions based on profits and recommends these attractions to the visitor until the budget time is reached.

3.2.2. Itinerary Recommendations

Research into itinerary recommendations has focused on discovering different types of itinerary recommendations based on the impacts of various constraints. These existing work objectives are to recommend itineraries based on specific POI visit order [40], group preferences [89, 90], mandatory POI categories [91, 92], demographic features [93], geographical check–in impact [94], etc. Notably, this research focuses on personalised user satisfaction instead of general satisfaction; thus, we avoid detailed explanations of general itinerary recommendations.

4. Personalised User Recommendation

Personalised interest is essential for recommendation research because it is relevant to various applications, including movies, sports, news, restaurants, and hotel recommendations. Personalised user interest has a significant impact on itinerary recommendations. In the following subsections, we will provide a detailed description of personalized itineraries and POI recommendations.

4.1. Personalised POI Package Recommendation

A POI package recommendation focuses on recommending a set of POIs so that users can visit all of these POIs within their budgeted time. Benouaret et al. [13] proposed a package tour plan aimed at tourists, with each package including personalised user interests and the popularity of different sets of POIs. Yu et al. [52] introduced personalised tour package recommendations utilising user preferences and spatiotemporal constraints, considering crowdsourced footprint data to develop personalised tour packages. Reddy et al. [95] designed travel packages for a group of users considering their common interests, social connections and other constraints. A graph-based model was proposed to recommend a set of personalised travel packages considering spatiotemporal constraints [96]. Chang et al. [97] applied a reinforcement learning-based reward function to rank a set of POIs and generate a successful tour package. However, all of these models recommend POI packages that are not in the form of an itinerary. The task of ordering these POIs into an itinerary is more challenging.

4.2. Personalised Next POI Recommendations

The POI recommendation model helps users to discover yet–unvisited POIs based on their interests. This model is beneficial to users as well as business authorities [98]. Collaborative filtering–based approaches such as matrix factorisation [99], Bayesian personalised ranking [100] and Bayesian probabilistic matrix factorisation [101] have been widely used in existing recommendation models. Researchers have shown that the effectiveness of POI recommendation is associated with POI geographical positions, users' visiting time, and users' social relationships [102, 103, 104]. These models assume that users who have visited the same locations have similar preferences. For a group of users, a sustainable tourist trip recommendation has been proposed using a multi-objective approach in [105]. Zheng et al. [106] introduced a deep reinforcement learning framework for online personalised news recommendations using state and action features representation. However, this approach is inappropriate for POI recommendations because spatial distance significantly influences POI recommendations. Thus, POIs and user latent features are used to predict user preferences for unvisited locations, improving recommendation performance. The work presented in [107] and [81] shows that the visiting and travelling time makes significant contributions to improving tour planning. A neural network framework for the next POI recommendation, *NeuNext* [108], was developed by leveraging POI context and using short and long–term preferences in unstructured data. Guo et al. [109] proposed location perspective-based neighborhood-aware POI recommendation instead of users perspective POI recommendation. However, the models mentioned above ignored the influence of queuing time in POI recommendations and did not consider user dynamic preferences.

4.3. Personalised Itinerary Recommendation

Personalised itinerary recommendation research has recently attracted significant attention due to its various applications. A number of existing research works have adopted a range of approaches to itinerary recommendation. Lim et al. [48] introduced the *PersTour* system for personalised itinerary recommendations based on trip constraints and visitor interest preferences, which were gauged using the duration of their stay at POIs. Debnath et al. [81] presented a time–aware and preference–aware routes recommendation system. Fang et al. [110] proposed a spatiotemporal information–aware mixture model that targets users within a specific geospatial range. Travel time is one of the most important factors in tour planning. Dolinskaya et al. [111] designed an adaptive and travel time–focused orienteering research problem with stochastic travel times, which finds the path among the reward POIs in an integral component of the decision space. The time constraint–based framework *pirT* [112] proposed a personalised itinerary in which social network features and social relationships are used to define visitor preference. Zhixue et al. [113] introduced a hybrid heuristic–based algorithm that applies a random simulation–based hybrid evolution technique in a time–variant stochastic environment to promote risk awareness among tourists. A collaborative filtering–based approach to nontrivial personalised landmark recommendation using geo–tagged photo was also proposed [114]. Bowen et al. [115] developed a crowdedness–aware route recommendation algorithm to predict the volume of visitors at a particular location over a given time. Notably, however, these itinerary recommendation approaches do not consider the queuing time of attractions.

Multiple attractive locations are scheduled to generate an itinerary recommendation where the order of places is essential. Baral et al. [116] proposed a recurrent neural network–based context–aware POI sequence considering visitors' personal interests. Multi–source–based personalised travel sequence recommendation [53] has also been developed; this approach can recommend a travel sequence rather than individual POIs using heterogeneous metadata. Lou et al. [117] focused on the sentimental characteristics of POIs, which are subsequently recommended to users via the *SPR* algorithm. Notably, the geographical position has a remarkable impact on POI recommendation [86] since visitors tend to visit POIs close to their homes or office. Several existing research works [118, 119] proposed probability–based recommendations, such that a POI closer to the visitor is more likely to be recommended. To explore the impact of spatiotemporal and social influence, the *STSCR* [120] model was proposed to handle user behaviours appropriately in sequential attraction recommendation.

4.3.1. Personalised Itinerary Recommendation with Queuing Time Awareness

Queuing time is another essential element of recommendation because of its real–life applications. Due to the COVID–19 pandemic [121], queuing time has become an increasingly important consideration; a fact that, surprisingly, has not been taken into account in most recent works. Moreover, queuing time significantly affects a personalised recommendation system in cases where a visitor has to wait for long periods before getting access to rides (i.e. a theme park tour). Theme park ride access requires a long waiting time, which may result in a frustrating experience for the users. There are works that aim to optimise queuing times among groups of users for itinerary recommendation [122] but do not consider user interest preferences. However, Lim et al. [47] combined queuing time with data collected from geo–tagged photos and introduced the *PersQ* algorithm by modifying MCTS for personalised itinerary recommendation. The *PersQ* algorithm aims to maximise user interest and POI popularity while minimising queuing time during itinerary recommendation. However, examination of the method shows that POI recommendation is inversely correlated to prior visitors' visit duration. In real–world scenarios, a longer duration of a visit to a POI expresses a higher level of visitor interest, which should be considered proportionally during POI itinerary selection.

The PersQ algorithm, introduced by Lim et al. [47], was the first to use the Monte Carlo Tree Search (MCTS) algorithm for itinerary recommendation as if it were a single-player game [123]. Prior to this, most researchers had applied MCTS to two-player games. However, the MCTS space increases exponentially with the number of iterations and nodes in the tree. Halder et al. [49] proposed efficient itinerary recommendation via personalized POI selection and pruning using an adaptive MCTS algorithm. Different pruning techniques have been proposed to reduce the MCTS space in two-player games, such as probability-based pruning [124, 125] and heuristic-based pruning [126]. In contrast, Neil et al. [127] designed a single-player game to transform an initial phase into a set of goal condition phases using automatic move pruning. Shu et al. [85] introduced a method to predict and estimate queuing time-based on positioning data.

5. Deep Learning Models in Itinerary/POI Recommendation

Recent deep neural models have demonstrated superior performance in the POI recommendation context. This section describes some of these deep learning–based recommendation models briefly.

5.1. *Recurrent Neural Network–based Recommendation*

Previous studies of POI recommendations have applied spatial and temporal [7] dependencies. Moreover, an attention–based spatiotemporal influence *ATST–LSTM* [10] model and self–attentive *SANST* model [128] have also been proposed. Check–in sequences and the contents of POIs were used in the *CAPE* [36] model. Zhou et al. [35] incorporated a range of different contextual information. Yang et al. [82] introduced a deep learning model named *PACE* for POI recommendation, which combined semi–supervised learning and CF to learn user preferences for POIs. The proposed *PACE* model considers various types of feature embedding relevant to the visitors and POIs. Wang et al. [83] incorporated Location–based Social Network (LBSN) images to enhance POI recommendation and proposed the VPOI model.

5.2. *Graph–based Recommendation*

Graph neural networks (GNNs) have attracted researchers' attention because they integrate node features from the connected neighbour nodes in deep neural networks. Some state–of–the–art works have used convolutional neural network (CNN) models [129, 130, 131] to capture spatial dependency. However, these CNN–based methods consider only grid–based linear spatial dependencies, which cannot adopt the complex topological structure of the POI network. To solve these problems, several recent works have applied graph convolutional network (GCN) [132, 133] for complex spatial networks, which was found to be very effective. However, these GCN methods only consider the topological relations within the road networks, such that personalised correlations between visitors and places are ignored.

5.3. *Reinforcement Learning–based Recommendation*

Reinforcement learning–based techniques can be categorised as model–based or model–free. Model–based techniques have a high time complexity and are therefore not suited to recommendation scenarios. Model–free reinforcement learning techniques are frequently used in the recommendation and can be further divided into two sub–groups: policy–based and value–based. The value-based techniques choose an action from all potential activities that maximises the Q-value. They rely on positive and negative user feedback for input, as described by Zhao et al. [134]. Zheng et al. [106] utilised duelling Q–networks to model state-action pairs. Therefore, if the number of actions is large, the value–based approaches are inefficient. The policy–based techniques generate a policy that takes states as input and then outputs an action. In policy–based models, the outcome is a continuous action representation ranked based on scores, after which the top–k organised scored activities are recommended to the users. Liu et al. [135] presented a deep reinforcement learning-based item/ product recommendation model that considers both long–term and immediate rewards when making recommendations. The model explicitly predicts interactions between items and users.

5.4. Transformers and Multi–task Learning

Transformer network-based models have improved accuracy across various natural language processing (NLP) tasks [136]. These models can capture all word dependencies in a sentence to predict the next word. Nowadays, transformer architecture has attracted increasing research interest due to its attention mechanism, which captures all dependencies at once using a non–recurrent encoder-decoder model. It has been shown that the transformer model is faster than both recurrent and convolutional layer-based models and improves performance using the multi–head self–attention technique [137]. Multi–task learning approaches have been used in a variety of research areas, including sentence classification and tagging [138], entity recognition and semantic labelling [139], and two different approaches to financial forecasting [140]. Yang et al. [140] utilised the transformer model to design a novel hierarchical volatility prediction using text and audio data in short and long–term conference earnings. To alleviate the data imbalance issue, *STrans* [141] was developed by leveraging inter–dependencies between space and time. Devlin et al. [136] proposed a deep bidirectional transformer architecture for NLP. The transformer allows multi–tasking, which relies entirely on the attention mechanism to compute its input and output dependencies. Hu et al. [142] proposed travelogues and check–in information based on multi–source data to capture user interests, find top–ranked itineraries, and recommend these to the users. However, these approaches are recommendation–based models that cannot utilise trip optimisation-related advantages. Inspired by transformer multi–task learning, Halder et al. [143, 144] utilised the multi–head attention–based transformer model to recommend the next top–k POIs while simultaneously predicting queuing time. Moreover, the multi–head attention model can capture relationships among POIs in multiple ways, thereby effectively handling user dynamic behaviours.

Halder et al. [145] have proposed a novel deep learning-based itinerary recommendation (DLIR) model that utilizes user temporal preferences to generate personalized itineraries. The model employs a candidate generator to produce the best candidate set of POIs based on the user's dynamic preference factors and scheduling requirements, such as queuing time and budget constraints. To capture user preferences accurately, the model considers recent, periodic, and trend patterns of user movement and introduces an adaptive GCN-based POI-to-POI relationship that can appropriately handle non-linear spatial relationships. This ensures that the model can effectively learn the user's preferences and movement patterns. Finally, a greedy policy is used to construct the full itinerary, where POIs are selected dynamically to maximize user interest while minimizing queuing time. Overall, the DLIR model proposed by Halder et al. [145] is a comprehensive and effective approach to itinerary recommendation that takes into account both user preferences and practical constraints.

5.5. Feature Embedding

Feature embedding is another essential factor in POI recommendation. In this context, the objective of feature embedding is two–fold: POI feature embedding and user feature embedding. The main objective of POI feature embedding is to develop an encoding technique for a POI network that effectively captures a POI's crucial properties (i.e., neighbourhood POI distance, recent check–ins, etc.). Similarly, user feature embedding is designed to learn an encoding model that can accurately capture users' visiting behaviour. Most existing works of this kind [10, 9, 143] have used unique user identity as a user feature; notably, an individual user identity cannot appropriately capture user behaviour because it cannot establish a relationship among visitors. This encoding is projected and processed into a low–dimensional space. Context–aware hierarchical POI embedding models using textual, visual, user and temporal features have been proposed in [36, 78]. Others have used language models such as Word2Vec and BERT for learning POI embedding based on sequences of POI visits [146, 147]. However, these models do not consider spatial influences. Several recent research works [148, 149, 18] have projected the item embedding process into a low–dimensional space based on the inner products of the features. Chen et al. [54] showed that using POI description-based similarity rather than only category–based similarity yields good performance and can efficiently handle new POI cold–start problems.

Table 2: Deep learning–based POI/Itinerary recommendation models.

Models	Spatio-temporal	User Interest	Queue Time	Technique	Multi-taksing
LORE [76]	✓	✓		Markov Chain	
ST–RNN [7]	✓	✓		LSTM	
APOIR [9]	✓	✓		Adversarial	
ATST–LSTM [10]	✓	✓		Attention + LSTM	
DeepPIM [78]	✓	✓		CNN & RNN	
STrans [141]	✓			Transformer	
MSTP–LSTM [142]	✓			LSTM	
HTML [140]	✓			Transformer	✓
CAPS–LSTM [116]	✓			LSTM	
TPM [150]	✓	✓		Probabilistic	
PTTR–Reco [81]	✓	✓		Brute–Force	
DCRNN [129]	✓			RNN	
T–GCN [130]	✓			GCN & GRU	
ST–ResNet [131]	✓	✓		CNN	
STGCN [133]	✓	✓		GCN	
STGN [108]	✓			LSTM	
TLR [143]	✓	✓		Transformer	
TLR_UI [144]	✓	✓		Transformer	
TLR–M [143]	✓		✓	Transformer	✓
TLR–M_UI [144]	✓	✓	✓	Transformer	✓
DLIR [145]	✓	✓	✓	Transformer + Greedy + GCN	✓
STaTRL [151]	✓			Transformer + Text Representation Learning	
STA-TCN [152]	✓			Temporal Convolutional Network	
POI_DBNBM [153]	✓	✓		Bidirectional Matrix + Deep Belief Network	
FedPOIRec [154]		✓		Federated Learning	
DCLR [155]		✓		Decentralized Collaborative Learning	

POIs recommendation has attracted interest from a broad spectrum of researchers because of its wide range of applications, which include tour recommendations, public safety and traffic congestion analysis [131, 156, 157, 158, 159]. These recommendations depend on user behaviour, spatial and temporal dependency, queuing and budget time. Recent deep learning-based POI recommendation models are summarised in Table 2.

6. Provider Satisfaction–based Itinerary Recommendations

Most POI recommendation approaches are only concerned with user satisfaction. However, fair recommendations must account for fairness on both the user and the provider side. Addressing only one side of satisfaction will result in an imbalanced user flow or will provide extra benefit to a particular provider. Thus, efficient recommendation requires provider satisfaction along with visitor satisfaction.

6.1. Fair Recommendation

Fair recommendation involves a multi–sided consideration such that all platforms are fair and unbiased. Serbos et al. [160] proposed a method for achieving customer individual fairness based on group tour recommendations on travel booking sites. Recent research shows that multiple unfairness and bias–related issues have arisen on different platforms. For instance, Hannak et al. [161] studied ethnic and gender biases in freelance marketplaces. Hort et al. [162] introduced semantically correct word embedding for reducing gender bias. Moreover, it has been shown that while popular POIs are usually visible to the majority of users, new but high–quality POIs often starve for follower visibility [163]. Several research works have focused on visitors' group fairness among customers and POIs. Suhr et al. [164] and Chakraborty et al. [165] introduced models to address the two–sided fairness combination problem. Patro et al. [166] proposed *FairRec*, a model that maps the product fair recommendation problem as a fair allocation problem to the POIs and customers. Liu et al. [167] proposed self-supervised learning for fair recommender systems. There are also some resource allocation models among the agents. Chen et al. [168] proposed a room allocation model in which precisely two persons are assigned to each room. Li et al. [169] introduced a room allocation model considering various room capacity and budget constraints with the goal of maximising social welfare. However, the room–sharing problem only considers users' unique preferences. Rahmani et al. [170] introduce a linear regression-based model using POI contexts that effectively captures the best combination of each user or group of users considering their previous historical interactions. Therefore, our problem formulations and proposed solutions differ from the existing models due to our inclusion of user spatiotemporal dependencies and POI capacity limits.

Table 3: Fair POI Recommendation based existing works.

Models	Users Interest	Producer/POI Exposure	Technique	Recommendation	Allocation
TOPK	✓		TOPK Interest	✓	
LOWK	✓		LOW-K Interest	✓	
Random	✓		Random Allocations	✓	
FairRec [166]	✓	✓	Greedy Algorithm	✓	✓
FairRecPlus [171]	✓	✓	Greedy + Cycle Free	✓	✓
CAFPR [172]	✓	✓	Demand Policy	✓	✓

Halder et al. [172] proposed a novel capacity-aware fair POI recommendation model that uses deep learning and allocation strategies to ensure maximum user satisfaction and appropriate POI allocations. The model comprises a deep learning model that captures user interest behaviors and a capacity-based user allocation strategy that ensures long-term POI service operations. The proposed model solves the recommendation and fairness problems in one framework by simultaneously learning user satisfaction and balancing POIs' exposure. This model ensures that both users and POIs are appropriately allocated and satisfied. Table 3 shows the existing fair POI recommendation literature.

7. Evaluation Metrics

In the tour recommendation context, evaluation metrics show how well the proposed models satisfy individual tourists. Previous works in tour recommendation have employed various evaluation strategies. In the next subsection, we briefly discuss different evaluation metrics.

7.1. Real–life Evaluation Metrics

We define a real–life evaluation strategy metric to facilitate comparison with real–life tour path history. In this paper, section 2 described methods of real–life tour path history mining from different sources, i.e., (i) location–based check–in, (ii) GPS tracking and (iii) geo–tagged photos. In all of these sources, we find a real–life POI visit sequence, which is compared to the recommended POIs to assess the model evaluations. The following information retrieval (IR)–based evaluation metrics are used to evaluate the performance of the recommendation model:

- **Precision:** The proportion of recommended POIs that belongs to visitors' real–life visit history.
- **Recall:** The proportion of real–life visit history that matches the recommended POIs.
- **F1–Score:** The harmonic mean of the recall and precision scores used to strike a balance between recall and precision.
- **Normalised Discounted Cumulative Gain (NDCG):** Evaluates the performance of the next POI recommendation based on its position rank in the recommended list.

In this evaluation, unique POIs are considered. Another variation of evaluation measures how well categories of POIs are recommended compared to real–life categories [173, 31].

7.2. Heuristic–based Evaluation Metrics

It is sometimes impossible to retrieve visitors' real–life visit histories. In these cases, we can use heuristic–based evaluation metrics to evaluate model performances. Moreover, we can use the following heuristic–based metrics to supplement the real–life evaluation metrics outlined earlier in Section 7.1.

- **Total POIs Recommended:** This metric represents the total number of POIs recommended to the visitor in their itinerary.

- **POI Popularity:** This metric summarizes the visitor's recommended POIs' popularity scores in the itinerary. It is also known as total tour popularity.
- **Tourist Interests:** This metric represents the summation of the visitor's recommended POIs' interest scores in the itinerary.
- **Maximum Queuing Time:** This metric indicates the ratio of queuing times to the maximum queuing time at recommended POIs in the itinerary.
- **Queue Cost Ratio:** This metric defines the mean queuing time value ratio to the total expended time in the itinerary.
- **Queue Popularity Ratio:** This metric denotes the average fraction of queuing time to POI popularity in the recommended itinerary.

In addition to these heuristic–based evaluation metrics, possible variations are the average, median, minimum, maximum, and quartile. The maximum and minimum tour interest scores represent the visitor group that is most and least satisfied with their recommendations, respectively.

7.3. Fair Recommendation Evaluation Metrics

To measure the performance of the recommendation model in terms of fairness, we apply user–side metrics and POI–side metrics. User–side metrics focus on user satisfaction with the recommended POIs, while POI–side metrics indicate the fairness of POI distribution among the user recommendations. We use the following evaluation metrics to evaluate fairness.

7.3.1. User–side Metrics

To assess the fairness of the proposed model for the users, we use the same personalised real–life evaluation metrics:

- **Precision@k:** Suppose that P_r is the next POIs in the actual visit sequence and P_k denotes the top–k recommended POIs. The precision represents the ratio of the next top-k POI that is present in the original next POIs as follows:

$$Precision@k = \frac{|P_r \bigcap P_k|}{|P_k|} \tag{6}$$

- **Recall@k:** We use the same P_r and P_k as above. Here, Recall@k represents the proportion of real next POIs that are also present in the top-k recommended POIs that is defined as follows:

$$Recall@k = \frac{|P_r \bigcap P_k|}{|P_r|}. \tag{7}$$

- **F1-Score@k:** This is the harmonic mean of both recall and precision of user u, defined as follows:

$$F1 - Score@k = \frac{2 \times Recall@k \times Precision@k}{Recall@k + Precision@k} \tag{8}$$

- **NDCG@k:** This evaluates the performance of next POI recommendation based on the position of the next POI in the result list. It is defined as follows:

$$NDCG@k = \frac{1}{U} \sum_{u \in U} \frac{DCG@k(u)}{IDCG@k(u)} \tag{9}$$

$$DCG@k(u) = \sum_{i=1}^{k} \frac{2^{Rel_u} - 1}{log_2(Ind_u + 2)} \tag{10}$$

where Rel_u is 1 if $hit@N = 1$ and 0 otherwise. Ind_u is the hit position index and takes values ranging from 0 to N-1. Finally, IDCG@k(u) is the ideal DCG@k(u), meaning that the index values range from 0 to k-1.

7.3.2. POI–side Metrics

As noted above, fair recommendation depends on user–side metrics and POI–side metrics. We use the following evaluation metrics to evaluate POI–side fairness and efficiency.

- **Capacity–based Fairness of Satisfied POIs (CFSP):** capacity–based POI fairness depends on the number of users allocated considering the capacity limit. If the user allocation of a POI is greater than the minimum percentage of capacity exposure, then the POI will be satisfied. The fraction of the satisfying score can be defined as follows:

$$CFSP = \frac{1}{|P|} \sum_{p \in P} Dem(p) \geq Cap(p) * min_{dem} \tag{11}$$

where $Dem(p)$ and $Cap(p)$ represent allocated users and capacity of p, respectively. Here, min_{dem} is minimum under demand threshold parameter.

- **Capacity–based Envy Free Allocation (CEFA):** User recommendation depends on users' personalised interests. Therefore, the POIs' exposure ratios are set in line with their capacity, preventing low–exposure POIs from losing market value and preventing envious of high–exposure POI. Thus, we calculate envy-free allocation score as follows:

$$CEFA = 1.0 - \frac{\sum_{p_i=1}^{P-1} \sum_{p_j=p_i+1}^{P} Envy\_Score(p_i, p_j)}{|P| \times (|P|-1)/2} \tag{12}$$

where, $Envy\_Score(p_i, p_j) = 1$ if two POIs p_i and p_j are not envy free. Otherwise, $Envy\_Score\ (p_i, p_j) = 0$.

- **Gini Index (Gini)**: This measures item frequency distribution inequality [174], e.g., number of users (exposure) in the POI recommendation context. Specifically, it measures POI exposure at the individual level. Given a set of POIs $P = \{p_1, p_2, \cdots, p_n\}$ and its exposure number $\{e_1, e_2, \cdots, e_n\}$. The Gini Index is calculated as follows:

$$Gini(P) = \frac{1}{2|P|^2 \bar{e}} \sum_{i=1}^{|P|} \sum_{j=1}^{|P|} |e_i = e_j| \tag{13}$$

where $\bar{e}$ is the average number of all POI exposure.

7.3.3. Balance Metrics between User and POI Sides

To provide a balanced consideration of two–sided matrices, we can rank metrics (incorporating NDCG and CEFA metrics) as follows:

- **Rank@k**: Rank metric indicates the average ranks of NDCG (user side) and CEFA

(POI side), which is expressed as follows:

$$Rank@k = \frac{1}{2}\{Rank(NDCG@k) + Rank(CEFA@k)\} \tag{14}$$

7.4. Online Controlled Evaluation Metrics

Many well–known online platforms (such as Facebook, Google, Microsoft, Amazon, Yahoo!, etc.) have applied online controlled evaluation metrics to experiment with the advantages of specific user interface and website design changes [175, 176, 177]. Online controlled experiments, A/B tests are used to perform these kinds of tests. This test measures the ratio of active users who have explored one template where another ratio of users who used another template. Tour recommendation websites, such as Booking and Expedia have also applied these online controlled tests before introducing new features. There are two evaluation metrics, as follows:

- **Algorithm-based Variants:** These variants evaluate recommendation performances among different tour recommendation algorithms (e.g., popularity–based recommendation vs. Naive Bayes recommendation and others in [178]).
- **Design-based Variants:** These variants evaluate user preferences based on website interface changes.

8. Conclusion

Itinerary recommendation is a crucial aspect of the tourism industry, which serves billions of international and national visitors. Personalized recommendations for next POIs and itineraries considering real-world constraints and budget time are essential for customer satisfaction. As the tourism industry grows, the impact of personalized tour recommendations on our daily lives increases, leading to a higher demand for personalized preferences influenced by multiple features. In this survey paper, we focused on real-life itinerary recommendations and discussed various contributions in the tour recommendation research. First, we discussed personalized tour recommendation problems based on different classical optimization problems that consider real-life considerations. Then, we explored user interest and queuing time-aware recommendation problems. Furthermore, we examined the fairness problem in the POI recommendation domain and proposed a solution based on deep learning technology. This study offers valuable insights into the challenges and opportunities in personalized tour recommendations. We also suggest exciting future research directions for improving the effectiveness and efficiency of itinerary recommendation systems.

9. Future Research Directions

In this survey paper, we studied various aspects of POI and itinerary recommendation. However, there are still numerous exciting directions for future research that could be pursued. This section briefly describes some limitations of existing research work and recommends some exciting directions for further study.

- In existing research, user interests were determined based on the number of captured photos and photo timestamps were used to estimate the time spent at POIs. Future studies may explore alternative methods for identifying user interests that do not rely solely on geo-tagged data. Additionally, previous research estimated queuing time based on historical data rather than real-time queuing records. Future studies could potentially develop a positioning-based queuing time tracking system to measure queues and queuing time in real-time. Furthermore, while previous research only considered walking time in itinerary construction, future studies may explore the inclusion of multiple modes of transportation, such as walking, bus, train, taxi, and car.

- Existing research studied the queuing time–aware top-k POI recommendation problem and solved the new POI cold–start problem. However, the models face challenges in solving new user cold–start problems. Future research could address this problem by adopting advanced deep learning based proposed model. Researchers consider POI description–based user interests to avoid categorical-based limitations. Therefore, under most circumstances, users could get recommendations from their friends and relatives, which could solve the user's cold-start problems. We infer that future researchers could consider user social relationships to solve new user cold–start problems. At the same time, adopting user sentiment while considering its features would be a good future direction. We believe that existing techniques can be adapted to solve these challenges.

- Scholars considered user temporal interest changes based on co-visiting and spatio-temporal features and therefore did not consider users' social networking influence for POI recommendations. Future research could incorporate social networking influence when recommending a full itinerary. The existing model is flexible in adding multiple constraints and can focus on all these constraints due to the attention mechanism.

- It has been shown that user distribution fairness is based on POI capacity, such that users get satisfaction and providers get enough users. However, they consider overall fairness in which real-time fairness impacts were not focused on appropriately. Under these circumstances, seasonal facility providers may receive unfair recommendations. Future research could apply seasonal fairness (e.g., summer and winter business) by updating deep learning model. Moreover, user sentiment analysis based on POI and itinerary recommendation would be a reasonable extension of deep learning based recommendation model. In sentiment analysis, user review comments are considered to measure their satisfaction level. Furthermore, future researchers could explain the reason for fairness, adapting existing proposed model in other domains to extend it to an explainable recommendation area.

- In this paper, we focused on personalised user itineraries but did not consider constraints for group or family tour planning. In the group tour recommendation context, group user sentiment incorporation would be an exciting research topic, where each user would receive maximum satisfaction, and the provider could quickly provide their services to the groups.

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Sajal Halder: Conceptualization, Investigation, Formal analysis, Writing - Original Draft preparation. **Kwan Hui Lim:** Validation, Writing - Review & Editing. **Jeffrey Chan:** Validation, Writing - Review & Editing, Supervision. **Xiuzhen Zhang:** Validation, Writing - Review & Editing, Supervision.

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