Fairness and Sustainability in Multistakeholder Tourism Recommender Systems

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ABSTRACT

In the travel industry, Tourism Recommender Systems (TRS) are gaining popularity as they simplify trip planning for travelers by offering personalized recommendations for accommodations, activities, destinations, and more. Ensuring fairness in TRS involves considering the needs and viewpoints of different stakeholders, including consumers, item providers, the platform, and society. Although previous research has focused on fairness in TRS from a multistakeholder perspective, little attention has been given to generating sustainable recommendations.

This doctoral thesis introduces the concept of Societal Fairness (S-Fairness) to consider the impact of tourism on non-participating stakeholders (society) such as residents, who may be affected by tourism issues such as increased housing prices, environmental pollution, and traffic congestion. The objective of this research is to contribute to the field of TRS by (1) modeling sustainability for societal fairness, (2) developing a fair multistakeholder TRS that balances sustainability concerns with other stakeholders while minimizing trade-offs, and (3) evaluating the approach through user studies and offline dataset evaluation to ensure user acceptance of recommendations.

CCS CONCEPTS

• **Information systems → Information retrieval**; • **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Multistakeholder Recommendations, Fairness, Tourism Recommender Systems, Travel, Information Retrieval

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1 INTRODUCTION AND MOTIVATION

Recommender Systems (RS) offer personalized content across various domains such as e-commerce, social media, news, and more, finding relevant information and avoiding information overload [1]. One of the areas where they are particularly helpful is travel and tourism as they simplify trip planning for travelers by offering personalized recommendations for destinations, accommodations, activities, and more [25]. This is a particularly challenging domain owing to the influence of dynamic factors like seasonality and travel regulations [6], as well as capacity-limited items such as airline seats, hotel rooms, and event tickets [3].

Traditionally, RS were designed to generate accurate recommendations for users. However, in practice, these systems serve as a meeting point for consumers, item-providers, and platforms, making it crucial to consider the interests of all stakeholders. Similar to RS, Tourism Recommender Systems (TRS) involve multiple stakeholders, such as transportation providers, hotels, and booking platforms, in addition to the traveler [1]. Each stakeholder has a vested interest in the traveler's journey, and optimizing recommendations for the consumer experience can benefit all parties involved [1]. However, there are instances where achieving the goals of one stakeholder may conflict with those of another, resulting in trade-offs [27]. To ensure fairness in TRS, it is important to adopt a multistakeholder approach that recognizes the interdependence between stakeholders and the need to balance their objectives.

Since tourism also impacts the environment, constructing a TRS requires considering recommendations that are sustainable. World Tourism Organization and United Nations Development Programme define *sustainable tourism* as "*tourism that takes full account of its current and future economic, social and environmental impacts, addressing the needs of visitors, the industry, the environment, and host communities*" [18]. However, achieving sustainability in the tourism industry demands interventions at several levels, including municipal policies, regulations, etc [53]. One effective intervention to mitigate the impact of tourism is to regulate the number of tourists to a destination, the area where TRS can be most useful. In particular, TRS can be used to prevent phenomena such as over- and undertourism. The terms over- and undertourism are used to describe situations where a destination is overwhelmed by too many tourists or lacks tourists, respectively. Overtourism harms the environment, locals, affordable housing availability, traffic congestion, in popular destinations, while undertourism negatively affects the tourism and hotel industries in the lesser-known destinations [12, 19].

While there has been some amount of research on multistakeholder fairness in TRS [45, 48, 54, 56], there has been limited focus on generating sustainable recommendations. To fill this gap, this thesis introduces the concept of *Societal Fairness*, or S-Fairness, in the context of TRS. S-Fairness considers the impact of tourism on non-participating stakeholders (society), such as local residents who may be affected by issues such as increased housing prices, environmental pollution, and traffic congestion. Here, we use the terms *sustainability* and *S-Fairness* interchangeably.

In this doctoral thesis, we aim to contribute to the field by: (1) modeling sustainability for societal fairness in TRS, (2) developing a fair multistakeholder TRS that balances sustainability concerns with other stakeholders while minimizing trade-offs, and (3) evaluating our approach through user studies, in addition to offline dataset evaluation, to ensure user acceptance of our recommendations.

2 BACKGROUND AND RELATED WORK

Given the multi-sided nature of TRS, evaluating it from a multi-stakeholder perspective is essential for ensuring that the system serves the goals of all stakeholders involved. The works by Balakrishnan and Wörndl [6] and Abdollahpouri and Burke [2] reveal that, multistakeholder recommendation and multi-sided fairness are closely connected in the context of tourism recommendations, as seen in Table 1. This table highlights studies that focus on specific fairness criteria and intra-stakeholder fairness for particular stakeholders. The main fairness criteria here ensures that the recommendations are equitable and unbiased for all stakeholders.

To address this, some studies have used a multi-objective optimization framework to optimize fairness concerns for multiple stakeholders simultaneously when generating tourism recommendations [45, 48, 54, 56]. Our survey paper [7] provides a detailed review of existing research on individual and multistakeholder fairness in TRS. Our research has shown that there is a lack of emphasis on generating fair recommendations that address S-Fairness or sustainability in the tourism industry.

In recent literature, there has been a growing focus on developing recommender systems driven by sustainability. For instance, Merinov et al. [38] proposed a multistakeholder utility model that optimizes travel itineraries. Their model employs recommender systems to promote under-visited areas and manage tourist flow in over-visited areas by distributing visitors across different points of interest. They also considered the trade-off between user preferences and time and occupancy of points of interest (POIs) by using a greedy breadth-first search graph method to recommend the most suitable travel routes. A case study of an Italian village was presented to illustrate their approach.

Research on over and undertourism in TRS is limited, but recent studies have highlighted the importance of using recommender systems to promote sustainable practices in local businesses. Patro et al. [43] proposed a multi-objective optimization problem that improved business sustainability, safety, and utility goals. Their approach used a polynomial time bipartite matching algorithm and was tested on real-world datasets from Yelp and Google Local. Pachot et al. [40] proposed a novel RS that considers territorial policies, promotes diversity, and provides a competitive advantage to service providers in order to address issues related to sustainable tourism practices. This system aims to boost business growth while also considering factors such as economic growth, sustainable production, and securing necessities for local authorities.

A major limitation of most of the related studies is that they were exclusively evaluated on synthetic data and simulated scenarios (as illustrated by Merinov et al. [38]) or using offline datasets [40, 43]. There is a lack of focus on user acceptance of the re-ranked or fair recommended results. Although Patro et al. [43] estimated customer preferences for restaurants using user surveys based on distance and ratings, there is no evidence that the users actually accepted their new approach. As a result, there is a need to focus on evaluating the acceptance of recommended results by users, which is currently not being addressed adequately in the existing literature.

3 RESEARCH QUESTIONS AND APPROACHES

While initial research has shown promise in the effective management of limited resources, there is a need to further investigate the impact of TRS on issues such as overtourism, undertourism, and the role of local authorities and communities in promoting fairness in recommendations. This doctoral thesis aims to explore the potential of TRS in addressing tourism-related concerns, particularly in the context of fair and sustainable recommendations.

In addressing this goal, we have formulated the following research questions.

RQ 1: What is the state-of-the-art for fairness in multistakeholder TRS?

Several studies have indicated the importance of fairness in multi-stakeholder RS in different domains [14, 51]. Despite this, there is still a need for a comprehensive review that synthesizes the existing literature on fairness in TRS. Therefore, we fill this gap by conducting a literature survey on the development of fair multistakeholder RS in the context of tourism.

We review state-of-the-art research on TRS fairness from multiple stakeholder perspectives, highlighting their main fairness criteria, and categorize stakeholders based on the criteria that apply to them. Finally, we outline the challenges, potential solutions, and research gaps to lay the foundation for future research in developing fair TRS.

RQ 2: How can we model sustainability for societal fairness in RS?

Tourism is a significant contributor to the economy and a source of income for many communities worldwide. However, its rapid growth has also resulted in negative impacts on the environment, local communities, and cultural heritage. To address these concerns, there is an urgent need to explore and adopt interventions that promote sustainable tourism practices such as recommending less popular and under-explored places and areas.

To achieve sustainability in tourism, it is necessary to explore a range of interventions beyond traditional municipal policies and regulations. This study aims to investigate the potential role of TRS in promoting sustainability in tourism. Specifically, we will explore interventions such as balancing the tourist load, promoting public transportation, encouraging carpooling, and supporting sustainable business practices.

Table 1: Table summarizing types of fairness and their associated stakeholders, main fairness criteria and their related works from the tourism domain (adopted from [2, 6, 7])

	Stakeholder			
Fairness Type	**Focus**	**Examples**	**Main Fairness Criteria**	**Related Work**
Consumer Fairness (C-Fairness)	the end users who receive or want to receive recommendations to plan their trips	tourists, business travelers, airline passengers	Individual Fairness [15]	[16, 24, 26, 47, 61]
			Group Fairness [36]	[13, 35, 44]
Item-Provider Fairness (I-Fairness)	the entities that provide the consumers with the recommended facility for their trips	hotels, resorts, rentals, amusement parks, tour operators, vacation companies	Popularity Bias [4],	[17, 28, 33, 41, 50, 52, 57, 63]
			Exposure Bias [5]	[8, 23, 30, 60]
Platform Fairness (P-Fairness)	the platform operator which hosts the recommender system	flight booking platforms, travel sites, e-commerce sites, hotel platforms, and similar systems	Ranking Bias [9]	[20–22, 29, 31, 32, 37, 64]
Societal Fairness (S-Fairness)	it represents the interests of the non-participating actors who are affected by the tourism activity but are not directly part of the TRS	local environment, city authorities, municipal councils, local businesses, and Destination Management Organizations (DMOs)	Sustainability [53]	[38, 40, 43]

Our analysis will focus on ways to ensure that all recommended tourist items receive appropriate exposure based on their quality, rather than being biased towards popularity, position, or exposure. We'll assess the environmental impact and ensure fair exposure for recommended destinations and establishments. Our research aims to create utility functions that model societal fairness in order to build a fair and sustainable TRS for the identified use cases.

RQ 3: How to balance societal fairness with other stakeholder concerns?

In RQ2, TRS may have unintended consequences for other stakeholders who are indirectly involved in the process of recommendation. This highlights the importance of a holistic recommendation process that considers the perspectives and interests of all parties, including society.

To resolve the challenge of ensuring fairness towards multiple stakeholders, many studies adopt a multi-criteria optimization approach. This method involves optimizing a utility function that accounts for multiple criteria and preferences of various stakeholders while aiming to maintain a minimal trade-off in personalization. This approach is commonly used in other domains such as movies or music [10, 11, 34, 42, 46, 49], but has not yet been widely adopted in the field of tourism. Additionally, most of these studies focused on satisfying the needs of consumers, providers, and/or platforms, without including society as a stakeholder. Our research, on the other hand, will use a multi-criteria optimization approach specifically designed for the tourism industry, optimizing for all four stakeholders identified in Table 1.

RQ 4: How should recommendations be communicated to the users?

Although multi-objective optimization appears to be a promising approach for ensuring fairness for all stakeholders, it often involves a trade-off with other criteria, such as reduced user satisfaction. This outcome is counterproductive as the primary objective of a recommender system is to recommend items that fulfill user needs.

While most studies evaluate their models through offline analysis or using existing datasets, there is a lack of focus on user acceptance of the re-ranked or fair recommended results. This is a vital aspect of recommender systems, as they must not only align with user preferences but also be fair to all stakeholders. Furthermore, we will investigate traveler types that are open to nudges towards S-Fairness and under what conditions. Our research will focus on user-acceptance of these fair recommendations and understanding of traveler preferences and personalities through conducting user studies and using explanations for the recommendations [39, 62].

4 INTERMEDIATE RESULTS AND CURRENT PROGRESS

4.1 Systemic Literature Review

We have addressed RQ1 by conducting a comprehensive review of the literature on fairness in TRS, focusing on both individual and multistakeholder perspectives. Our analysis highlights the scarcity of works that incorporate society as a stakeholder in defining the main fairness criteria, indicating a need for future attention in this area. The work [7] has been accepted for publication.

4.2 Preliminary Work

Master's thesis on Exposure Bias

This doctoral thesis builds upon my master's thesis which was written in collaboration with TU Munich and the Max Planck Institute of Software Systems, Germany. It focuses on exposure disparity in location-based searches. Through analyzing data from Google, Yelp, and Booking.com, we discovered that highly rated establishments often receive less exposure than they deserve, which can lead to economic harm. Popularity and position bias are the main factors contributing to this disparity. The works of Banerjee et al. [8] and Patro et al. [43] are derived from this thesis.

User Studies

Together with a student, we are developing a user survey where we explore how sustainability considerations can compensate for less popular places. Our intermediate findings show that offering more sustainable but less popular options in a list of recommendations increased the likelihood of users selecting a sustainable option, while only slightly decreasing user satisfaction.

Although these studies are preliminary and use simulated data to gauge initial user acceptance of environmentally friendly recommendations, they contribute to our understanding of how to integrate societal concerns into TRS. This is a crucial step in addressing RQ2, RQ3 and RQ4.

Dataset Acquisition

To address RQ2, and RQ3, we explored multiple potential data sources that can be utilized. Our approach involves amalgamating data from diverse public sources such as Google Directions API's public transport information and Airbnb [1] to suggest solutions that promote sustainable tourism practices. Furthermore, we have established a collaboration with OutdoorActive [2] and intend to leverage their data on outdoor activities in the Alpine region for our investigation. We have already conducted preliminary research on some of these sources and they seem to hold potential.

5 EXPECTED NEXT STEPS AND LONG-TERM GOALS

Our next step is to explore potential methods for implementing tourist load balancing mechanisms to address both over and undertourism. The initial plan is to investigate the Foursquare check-in data [58, 59] for major cities such as New York and Tokyo in order to simulate Google's popular times [3]. By analyzing this data, we can calculate the hourly or daily check-in count per venue to determine the crowdedness levels. Moreover, we aim to produce sustainable recommendations by combining this information with restaurant ratings. During peak hours, we strive to suggest less crowded venues with comparable ratings and from similar categories to reduce the load and limit environmental impact.

To tackle RQ3, we plan to develop a multi-objective optimization framework that considers fairness concerns for all stakeholders, including society. Our approach is inspired by the work of Wu et al. [55], which we will use as a starting point. However, unlike their model that only optimizes for item-providers and consumers using the MovieLens [4] dataset, our proposed framework will optimize for all four stakeholders identified in Table 1. We will use data from Yelp businesses to build our model. Our goal is to ensure a more equitable and socially responsible recommendation system by addressing the interests of all stakeholders. This multi-objective optimization framework is the first step in achieving this goal.

Our final step is to evaluate user acceptance of the recommendations once we have determined the utility functions for including society as a stakeholder and the tradeoffs it causes for user satisfaction. The recommended item may not be the best match for the user's needs, but it should be acceptable while also being more environmentally friendly. To achieve this, we plan to integrate our fair TRS into a practical prototype application and conduct user studies to evaluate their acceptance. One potential challenge we face in achieving high user acceptance is that users may not fully understand the reasoning behind the recommendations. To address this, we plan to explore ways to generate explanations for the recommendations, by leveraging existing research in the field of explainable AI [39, 62]. By providing clear and understandable explanations for why a particular item is being recommended, we believe that we can increase user trust in the system and ultimately improve user acceptance.

6 CONCLUSION

Addressing fairness in multistakeholder TRS is crucial, but often this issue is examined solely from the perspectives of consumers or platforms, without considering sustainability concerns. To overcome this limitation, we aim to develop sustainable recommendations that cater to society as a stakeholder. Our approach not only involves empirical data analysis but also includes user studies to validate our results and ensure user acceptance of our recommendations.

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