Multistakeholder Recommender Systems in Tourism

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Tourism recommender systems have experienced huge growth over the years, but so far have not satisfactorily considered the process of recommendation as it affects parties other than the end-user. In this paper, we outline approaches and considerations that are of importance when multiple stakeholders' interests are taken into account in a tourism recommendation framework. We also propose a mechanism for quantifying external influences outside the control of the recommendation environment in stakeholder-aware tourism recommendation use-cases. The concepts introduced are evaluated by means of a user study based on a simulated recommender system based on Airbnb listing data, and we find that end-users of a tourist recommender system are sensitive to other stakeholders' interests and largely depend upon the help of the recommender system when dealing with external, non-functional influences.

CCS Concepts: • **Information systems** → **Recommender systems**; • **Applied computing** → *E-commerce infrastructure.*

1 INTRODUCTION

Tourism is one of the largest social forces on earth. Annually, millions of people travel for leisure, giving rise to an industry that adds vast sums of revenue to the global economy. With the rapid progress of the information age, it is only natural that the tourism industry is also well served to embrace the advantages brought on by new technology. The democratisation of information however also brings its own challenges, and it has become increasingly harder to connect consumers with providers due to the sheer volume of information produced by both parties; which is certainly the case in tourism as well.

Recommender systems solve this problem in an elegant manner by making sure interested parties always find what best fits their needs. It has already been argued that rather than recommender systems considering the end-users' aims as the core objective, the interests of other related parties should also be studied and evaluated.

Unfortunately, the study of multistakeholder aspects of tourism recommender systems remains a fairly ill-explored area in current literature, even though it is clear that the tourism industry is greatly enhanced by the incorporation of explicit multistakeholder constraints when user-facing systems are designed and implemented. Tourist recommender systems frequently need to deal with a variety of (sometimes conflicting) objectives set forth by various powers that shape the overall landscape of tourism.

In this paper, we embark on a study of tourism recommender systems from the lens of stakeholder-aware recommendation. We apply the topics found in previous literature to the topic at hand when necessary, and introduce concepts such as the categorisation of external factors which apply to the recommendation process in the form of unforeseen influences. We further conduct a user study based on synthetic recommendations from Airbnb data to put the concepts we discuss to the test and see how receptive end-users appear to be to ;as well as to gauge the respondents' views on concepts important to mustistakeholder tourism recommendation.

The paper is divided into five broad sections, with a brief overview of multistakeholder recommendation making up the next section. Then, we discuss concepts applicable to multistakeholder tourism recommenders in section 3, while section 4 is devoted to the particulars of the user study we have undertaken. Section 5 summarises the results; and closing remarks as well as future outlook of the area make up the sixth and final section.

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2 MULTISTAKEHOLDER RECOMMENDER SYSTEMS

Multistakeholder aspects of recommender systems have been considered by previous research even before the term itself was coined. For instance, the RECON online dating recommender system [15] has multistakeholder aspects, where the reciprocity between parties can be seen as a facet of user/user and user/provider interaction. However, in most of such cases, the multistakeholder aspects were seen as a special case where additional considerations come into play, as opposed to the standard operation practised by single-dimensional recommender systems. Abdollahpouri et al. suggest however that rather than being a special case, multistakeholder recommender systems represent the general case [2], where the multiple roles played by a recommender system are only served in a satisfactory manner when the interests of the other parties are taken into account in the overall scheme of recommendation. The authors further liken this change of view to one that occurred in microeconomics near the turn of the century [16], where the concept of multi-sided platforms was introduced to the benefit of easier economic analysis of new and existing systems.

In a later work, Abollahpouri et al. [1] identify three classes or stakeholders commonly seen in recommender systems:

- Consumers: the consumers (users) are the end-users of the recommender systems, based on whose interests and search criteria the recommendations are made. More often than not, these users play an active role in the recommendation process. Even when they are not actively specifying their interests and/or selecting items based on preference, some of their heuristics may be taken into account when constructing the recommendations for them (also called implicit feedback).
- Providers: the item providers, i.e. the entities which produce or manifest the item. These are the parties that "stand behind the recommendation items", be it manufacturers, producers, sellers, renters and the like. In many cases, the providers will be the primary set of stakeholders who gain monetary benefit at the end of the recommendation process, which could be from an actual item sale or booking.
- System: the recommender system itself, or in other words the set of parties that provide the recommendation service and apparatus. In most cases, the system will control the algorithms and metrics used for producing the final recommended set of items. The recommendation service providers might also play the role of provider in certain conditions, such as in the case of direct sales.

Additionally, in a review of modern multistakeholder recommender systems [8], Jannach and Bauer introduce another stakeholder: society.

- Society: the outside environment at large, which may include legal authorities, local governments and similar entities. In addition to having an impact of the recommendation process, the authors also suggest that the society itself may also be affected in cases where the recommendation process has greater real-world ramifications, such as social media and global news. The examples provided by them in this case include filter bubbles and echo chambers, which are phenomena in sharp focus today [6].

It is worth noting that in certain situations, stakeholders play more than one role in a given scenario (for example, in an e-commerce setting, the same entity may act as the provider and the system at the same time). In such cases, these stakeholders are usually considered separately, as though they are different entities.

3 MULTISTAKEHOLDER ASPECTS OF TOURISM RECOMMENDER SYSTEMS

In multistakeholder tourism scenarios, there may exist various kinds of real-world actors with a wide variety of aims, some of which may temporarily or permanently align with the aims of other parties. Hence, it is imperative that attention is paid to the dynamics of the stakeholders when defining a recommender system.

3.1 Stakeholder Dynamics in a Tourism Recommender System

Following the classification of common stakeholders encountered in a generic multistakeholder recommender system from Jannach and Bauer [8] we generalise the type of stakeholders encountered in common touristic recommendation scenarios as specified in Table 1.

Table 1. Classifying stakeholders for travel recommendations.

Stakeholder Class	Stakeholder
User	Travellers, airline passengers, tourists, hotel visitors, backpackers, campers, hikers/trekkers, park visitors, festival attendees.
Provider	Hotels, national parks, resorts, rentals, amusement parks, airlines, tour operators, vacation companies.
System	Flight booking platforms, vacation recommenders, city information systems, travel sites, e-commerce sites, hotel platforms and similar systems.
Society	National parks, city authorities, municipal councils, airports, tourist sites, game reserves, nation states.

In addition to stakeholder classification, it would also be advantageous to consider interactions between stakeholders which may help find trends that can be used in the recommendation process. For instance, the interaction between the users and the provider would either be in the form of selection of itemsets such as the user receiving a set of recommendations; or directly monetary transactions (i.e, bookings or reservations at the end of the recommendation cycle). In each case, these interactions could be formally defined and incorporated into the stakeholder-aware recommender system during the design phase. In the first case, the itemset recommendation could be made multistakeholder-aware by introducing the interests of other stakeholders such as the system or society into the process. Such systems could take into account the budget considerations (and limitations) of tourists when recommending hotels and restaurants, and could introduce special offers to increase the likelihood of successful conversion (to benefit the system) or even to incentivise would-be consumers to choose other rarely-chosen items. In the second case of concrete transactions, the recommendation process is assumed to have been concluded and the stakeholders are about to enter a contractual relationship. Here, successful representation of inter-stakeholder interaction could be used to establish patterns and identify hidden trends. For example, if it is detected that a large number of tourists who were searching for beach resort recommendations end up buying package tours to the Bahamas, it can serve as a baseline to improve further recommendations by recommending beach vacations to the Bahamas for tourists searching for holiday recommendations, since a common pattern has been identified which is likely to lead to successful conversion.

Zheng's work on the applications and challenges of multistakeholder recommender systems [19] touches upon the need to balance utilities among stakeholders. The author compares the newer multistakeholder approach to studying conflicting forces in recommenders to the more traditional multi-objective recommendation, with the added caveat that the "objectives" could be repurposed to cover not just the end-users and therefore could be useful to model multiple distinct stakeholders as well. The author further suggests that there could be cases of multiple utilities at play per stakeholder, rather than one overarching utility, which would mean that the gain of one utility could mean the direct/indirect loss of another for a given stakeholder.

Contrasting with considering the gain of utilities to both parties, there are also cases where the increase in one party's utility may serve to directly or indirectly decrease the utility of another. We categorise this phenomenon as inter-stakeholder and intra-stakeholder forces, as follows:

- Inter-stakeholder: The utility gain of one stakeholder may serve to affect the utility gain of another stakeholder (usually negatively). In other words, this type include cases where one stakeholder must "lose" for another to win. For example, in a recommender system which prioritises user gain over others, sustained discounting to promote conversion may lead to long-term loss of utility to the provider or system. In tourism use-cases (unlike music or film recommendations), it is common that the user only needs the recommender system fewer times a year; which could lead to short/medium term utility loss to other stakeholders. That is, a vacation is much less frequently sought than music, so a highly successful recommendation will essentially satisfy the user's need which consequently means the user is lost as a consumer till the next trip (medium term loss of utility to both the system and possible providers).
- Intra-stakeholder: Unlike in the previous case, the utility gain of a particular member of a particular stakeholder class may also affect the utility gain of others within that same group. In other words, for one party to "win", another party must lose *within the same stakeholder class*. This can be seen in multistakeholder-aware tourism recommendation scenarios in various ways, such as when one tourist scoring a limited discount for a particular resort means that another tourist loses out. Not limited to users, this can affect other stakeholder classes also, such as providers. namely, in reciprocal tourist recommender systems such as Airbnb, providers compete with one another to list their offer for potential travellers to choose. Thus, one rental being selected at the end of recommendation by a customer means a loss of utility to other rental providers.

This leads us to reason that a multistakeholder recommender system should be aware of the interplay between different stakeholders not only in their interactions but also their utility gain/loss as well. Value-aware recommender systems [14] focus on the gains of utility of the user as well as itself; and in a multistakeholder perspective will be aware of values to other parties as well [1]. Hence, a value-aware paradigm in designing multistakeholder recommender systems for tourism use-cases will be a good start in ensuring both inter- and intra- stakeholder gain is maintained.

3.2 Explanation of Recommendations and Transparency

Continuous improvements in recommender systems research mean that more focus is also being given to the possible pitfalls and shortcomings affecting recommender systems of old, one of which is the transparency of the system itself. Traditionally, recommender systems have been seen as black boxes consisting of thousands of variables, which all act in arcane ways to produce a particular set of recommendations, as described by Jannach et al. [9]. The authors argue that the recommender system should offer an explanation (or at least an intuition) as to why a particular itemset has been recommended to the user, thereby fostering trust in the recommender system. The advantage of this view is clear: the user feels less alien and is able to see how or why his/her input could shape the results presented. Then, the user would be more inclined to offer feedback on this process if any of the assumptions taken for the recommendation turn out to be not entirely accurate. According to the authors, the feedback could be used to improve the recommendation and make it more relevant to the user [3], as well as allowing the user to take control of the recommendation process rather than be a bystander. The authors also describe two ways for this increased user interaction: during the requirement elicitation phase (i.e. when the user's implicit and explicit input is taken as a source for recommendation) as well as during the recommendation presentation (where more explicit feedback could be asked). A similar sentiment is shared by other studies as well, such as in [17].

From a multistakeholder standpoint, offering recommendation explanations in tourism recommender systems has the distinct advantage of promoting user trust. In most cases, recommendations offered as part of tourism recommender

systems contain separate sorting (or presentation) methods for highlighting "recommended" or "top picks" items. Here, the recommender system operators either rank items based on past data or even based on other forms of compensation from the providers. This compensation is usually in the form of commissions or even special deals or discounts to entice users to consider such items over others.

The fact that other stakeholders' interests and aims affect the users' ultimate result would be a cause for concern for some users if left unexplained. Conversely, providing explanation to the effect the results and their ranking may be affected by commissions which will undoubtedly aid in generating trust, further improving the standing of the recommender system in the users' eyes.

3.3 The Case for Considering Non-Functional Influences

Compared to recommender systems in other domains, tourism recommender systems are susceptible to external influences that may not play as big of a role in other cases. Travel restrictions and touristic trends play a huge role in driving the industry's direction per season, and some such influences may also change the entire landscape of the industry on a permanent basis.

Let us illustrate this phenomenon through the recent COVID-19 pandemic which crippled recreational travel. Consequently, tourism was one of the most affected industries worldwide, with an overall projected loss of 74% international tourist arrivals in the year 2020 compared to the previous year [18].

It is therefore reasonable to expect that the performance, reach and demand for tourist recommender systems will also be affected by these external factors. In a multistakeholder tourism recommendation use-case, it can be inferred that considering the impact of external factors would greatly enhance most advantages brought to the table by recommender systems , including user satisfaction, increased conversion rates and provider exposure. Unfortunately however, this is a topic that remains unexplored in literature, with most forays into multistakeholder recommendation (including tourism) following the trend of exploring algorithmic approaches and fine-tuning results. To counter this fashion and to reinforce the suggestions from Jannach and Bauer on the previously described McNamara Fallacy [8], we propose that the study of external influences in stakeholder-aware tourism recommender systems be characterised and studied. To this end, we divide the type of external influences into four major groups based on the duration and predictability of the effect: *constant*, *deterministic recurrent*, *non-deterministic recurrent* and *volatile*.

3.3.1 Constant Influences: the first type of external influences with the possibility of having a lasting effect on the recommendation process is termed constant influences. This could be anything from national laws or local rules that could render some part of the recommendation process infeasible or unlawful. In other words, this type of non-functional influence statically affects the recommendation process and can be understood clearly through analysing existing rules. The distinguishing characteristics of this type of non-functional influence are the period of introduction (which tends to be gradual or pre-specified), as well as the ability for the stakeholders to deal with them (commonly in the form of static responses). An example for this would be the recent ban of cruise ships from the lagoon in Venice, Italy. This would render all recommendations of cruise travel to the historic Venetian city centre invalid.

In multistakeholder situations, constant influences have a chance to affect all possible stakeholders. On the user's part, they will be directly affected by getting a reduced/amended selection of recommendations, or even not having items recommended to them based on the condition. For providers, it may be that their item or service on offer might have to change based on whether or not the influence demands it. The system might have to make change on the

recommendation process or even introduce additional steps. This is especially relevant in travel recommendation, given the nature of items and experiences on offer as well as the propensity of such items to change through external factors.

3.3.2 Recurrent Influences (Deterministic): the next type of non-functional influence repeat over time with some period and cause a corresponding effect, as opposed to being static changes. Here, the period of occurrence can range anywhere between days to decades. For instance, the high season for a particular beach may take place at the start of springtime, which is annual and is usually deterministic in that it is possible to predict the behaviour of potential tourists with reasonable accuracy (hotspots, popular activities etc). Similar to constant influences, the changes taking place due to these non-functional influences can be understood via study of historical data as well as extrapolation based on the growth of other factors.

Considering multistakeholder tourism recommendation use-cases, similar to constant influences, it is usually feasible to balance stakeholder utilities using predictive measures. For the users' standpoint, a recommender system aware of touristic seasons would provide much better quality recommendations than a generic one. Moreover, users might be accustomed to receiving seasonal offerings from real-world outlets (such as brick-and-mortar stores), so they might tend to expect the same from automated, computer-based recommender systems as well. For the providers, season-aware travel recommender systems could introduce an added layer of advantage where items not highlighted during a particular season may be brought up when the time is right. A good example is a beach resort gaining increased visibility when the aforementioned high season starts, when it was featured less by the recommender system during winter. For the system itself, it is clear that better quality recommendations and increased provider utility will bring benefits from both ends.

3.3.3 Recurrent Influences (Non-deterministic): in addition to the above case, there may be instances where the effects posed by periodic influences are not reliably measurable and repeatable. In this case, it would be best to consider such influences separately and develop strategies to deal with them more effectively rather than follow a set plan more suited to handling deterministic influences. Specifically, in cases where it will be difficult or impossible to predict the outcomes of a particular constraint introduced by a periodic change with an acceptable measure of accuracy, such changes could be characterised as recurrent non-deterministic influences and dealt with as such.

Compared to deterministic influences, these influences are much harder for a multistakeholder tourism recommender system to predict and deal with. The mechanisms for handling such cases lean more towards reactive feedback, where even though the nature and period of the influences are known, the actual effect played by them may only effectively be addressed by looking at how things develop and then dealing with them. Interestingly, users are the party who are least affected by such influences on a recommender system, as they simply tend to associate the change with the society and climate rather than the recommender system that gives them suggestions. However, successfully predicting such cases and making users aware would go a long way towards promoting trust of recommendations and dependability. Providers on the other hand are also more inclined to react to situations, and would be similarly well-served by a recommender system aware of the changes, such as in the case of increased mosquito presence, where a tourism recommender system could potentially alert the provider that their listing needs to make amends to combat this influence.

3.3.4 Volatile Influences: the final type of non-functional influences that we define are the so-called volatile influences. Such influences are the ones that occur suddenly, often without warning or reason, and which offer no reliable way to predict or handle the exact outcome of the influence with any measure of confidence. These influences also fit neither

of the above discussed groupings: in that they are not usually deterministic, as well as not having a discernible period of effect.

The ongoing COVID-19 pandemic of 2020/2021 is an example to this type of non-functional influence. By nature, the pandemic was largely unforeseen and did not occur with any detectable periodic oscillation. Moreover, it is impossible to predict with any certainty what might happen if given as input a particular situation, and given the same input parameters, it is impossible to come up with a particular outcome in a procedural manner. Similar volatile influences could arise from cases such as warfare, civil unrest, sudden seasonal changes and similar circumstances.

For stakeholder-aware travel recommender systems, this type of external, non-functional influences is the one that is most difficult to deal with effectively. All stakeholders can be expected to be in reactive mode, with little or no predictive measures possible to be taken up to ensure the smooth functioning of recommendation performance. Items and experiences that were perfectly good to be recommended could potentially be rendered useless, and utilities of stakeholders could interact and affect one another in unforeseen ways.

4 EXPERIMENT METHODOLOGY

To explore the perceptions of the concepts we have discussed above (specifically from the user's perspective) in real-world use-cases, we conducted a user study. We selected a hypothetical trip to the city of Amsterdam in the Netherlands for tourism purposes as the backdrop, and posed questions to the study participants who were put in the position of someone looking to book an Airbnb[1] stay in the city.

To achieve this, we first obtained a dataset of scraped Airbnb listings [13] which contained records of various forms of accommodation available for hire in the city of Amsterdam. The dataset, which initially contained 494954 records, was cleaned and processed, which involved removing redundant fields and making sure that all records relevant to the topic had homogenous data. Then, new fields were also created based on calculations from existing fields (for example, a price-per-head field being created from the price and size of the record). Next, several synthetic recommendations were constructed from this data, with each recommendation representing a reranking of results based on particular criterion. The respondents were then presented with these recommendations, which they were asked to first rate based on how much they match their expectation on a Likert scale [10]. They were also offered the chance of providing text input as to why they selected a particular response.

The ultimate aim of this part of the study is to explore the impact of the other stakeholders' actions on the utility gain/loss of the user, and we define the stakeholders are as follows:

- User: the survey respondents play the role of the user of the recommender system, where they interact with the presented recommendations. In this scenario, users' actions that are usually tracked by a recommender system such as mouse movements, length of stay in a particular recommendation etc. were not checked. In place of such indirect measures, users were directly asked for their opinion in the form of a free text area.
- Provider: the provider in this case is the Airbnb host whose property is listed for stays. The listings represent the recommended items to the user, and the provider gains utility when their particular listing is chosen.
- External parties: in our scenario, we model an external party in the form of the City of Amsterdam, which is assumed to have motives of its own which affects the nature and quality of recommendations shown to the users.

[1] http://airbnb.com

- System: the recommender system itself will play the role of the system. Here, we not only consider the system as a passive entity, but as an entity with vested interest in the recommendation process, such that the system is defined to benefit when a recommendation is selected by the user for a stay in the form of a successful sale.

In addition to offering concrete cases of recommendations, we also explored the users' views on various topics relating to tourism recommender systems in a multistakeholder point of view. Here, we study factors such as whether they are aware of the impact of the other stakeholders on the nature of the recommendations they receive, as well as their perceived impact of non-functional influences on the recommendations.

4.1 Reranking Airbnb Listings

For the first static recommendation shown to the user, we defined a set of criteria as the users' aim in obtaining recommendations and sorted the dataset accordingly. Specifically, this reordering of the data is aimed at finding the cheapest, best rated listings which are closest to the city centre, which was assumed to be the co-ordinates of the National Monument[2] in the De Wallen district. To deal with conflicts arising from sorting by these three disjoint fields, the closest listings to the city centre were prioritised first (sorted ascending by distance), which were then ordered by price (ascending) and then by rating (descending).

The resultant recommendations in graphical form as presented to questionnaire participants can be found in Figure 1.

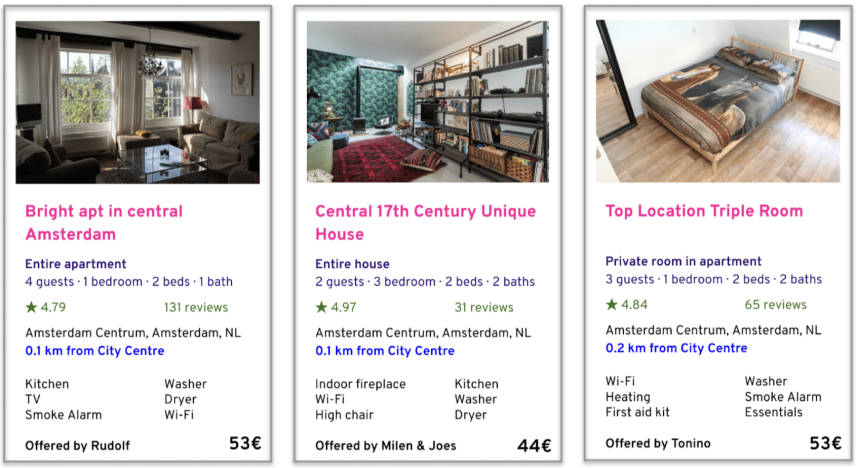

Fig. 1. Generated recommendations exactly matching users' assumed priorities.

In the second scenario, we rerank the results from the above scenario based on increase to perceived provider utility. To this end, we assume that listing provider will likely mark their listing price high when they believe their property value is higher, owing to a number of reasons (such as location, neighbourhood, amenities etc.). Then, reranking the results using the price per square feet metric, we attempt to implement this reasoning where the listings with higher price per square feet are inductively be thought of as offering more profit/value to the host. As a result, compared to case 1 the prices of displayed listings as well as the distance from city centre have increased.

For the third scenario, we model the interests of the City of Amsterdam. It has already been the focus of in various studies [7], [4] that Amsterdam, as a city at risk of being overwhelmed by mass tourism, has started various measures

[2] `52.37298331479081, 4.8936054723836815`

to bring balance between the city's resources and eager tourists. Even Airbnb's role in providing easy access short stay rentals have been the focus of contention [11]. Hence, it is not difficult to hypothesise that with ever increasing tourist numbers, the city stands to gain by limiting rentals in locations with high density of attractions. Consequently, we assume that the city's utility is set to increase by disallowing rentals in the very centre of the city. This essentially creates a blanket of about 2km over the centre of the city as an Airbnb-free zone, and consequently the listings are now much farther apart from the city centre, which is in direct contravention to the requirements set forth for the users. The prices in the outer areas are generally cheaper than the centre, and this is reflected in the results accordingly.

In the final scenario, we target the utility gain of the recommender system as a whole. It has been proposed that the utility of a recommender system itself stems from the increase of utility of its clients (in most cases the item provider and the consumer) [1]. However, many value-aware recommender systems are in fact profit motivated and aim to increase their utility by direct monetary gain [5]. For instance, the recommender platform proposed by Nguyen et al. [12] earns a monetary commission from providers. Our use case is of the second kind, where Airbnb as a business entity earns revenue through commissions made through bookings made on its site. Hence, we also treat the simulated recommender system that we use in the study as profit-oriented and assume that the most booked (most popular) listings are the likeliest to be converted into a successful sale; and offer these listings as the final recommendation for this case. Here, we infer by interpolation that the more reviews that accumulate per month for a listing, the more bookings it achieves; and therefore rerank the data with emphasis on reviews per month. It is also worth noting at this point that these listings are also usually displayed prominently in the real Airbnb site as most popular, which adds weight to our assertion that the system itself is most likely to gain monetary utility from such listings.

4.2 Opinion Survey

In the next section of the questionnaire, respondents were presented with a set of statements concerning tourism recommendations and were then asked to give a rating based on to which degree they agreed/disagreed with these statements. The provided statements covered topics ranging from their willingness to use interactive recommender systems particularly for tourism use cases to users' perception of their own utility.

4.2.1 I prefer to use interactive recommender systems for tourism use-cases rather than other sources (friends/family, adverts): we ask respondents whether they prefer to use interactive recommender systems over other traditional sources. A higher proportion of users responding positively means a larger share of the target audience being comfortable with recommender systems and a consequent indication that the current rise of Internet-based recommender systems in almost all end-user-facing areas is also very much applicable to tourism use-cases as well.

4.2.2 As a user, I accept that sometimes other factors will cause the recommender system to show me results that don't perfectly match my requirements: here, we verify that respondents are indeed aware and accept that other stakeholders play a role in their recommendations, especially from a tourism standpoint. We also suggest the user that some recommendations may not match the search criteria perfectly and attempt to gauge the feedback. Here, a higher positive response will not only point to increased awareness of external factors, but also affirmation of the trends where recommender systems sometimes may place other parties' needs at the same level as users'.

4.2.3 As a user, I believe that a recommender system should prioritise my needs over other parties such as rental providers etc.: next, we check if more users prefer to be the focus of recommendation or if they are willing to accept emphasis of other stakeholder interests. Even though it may not be readily evident, most recommender systems users are of the

belief that the tools they use ultimately exist to further their benefit, and through this question we check to what extent the respondents also agree with this sentiment and consider the recommender system as something that should put their needs above other stakeholders.

4.2.4 I believe that a recommender system should tell me when interests of other parties are taken into account when giving me choices: as a follow-up of the previous two questions, we explore the level of trust respondents are willing to place on recommender systems they are accustomed to. In standard recommender systems, user trust is usually maintained by disclosing when other factor impact the final recommendation (such as monetary commissions or adverts). As we have seen previously in section 3.3 however, in stakeholder-aware recommendation the whole nature of recommendation hinges upon balancing utilities and therefore it becomes even more important to be transparent. Through this question, we gauge the users' intent on how this should be handled in such cases.

4.2.5 I am OK with the data I provide for recommendation being used for improving the recommendations of other users like me, as well as benefit other parties: we touch upon privacy and ethical aspects of using the recommendations resulting for one particular user to improve the output for another user in a multistakeholder recommender system oriented towards tourism. Common techniques used in contemporary tourism recommender systems (such as collaborative filtering) factor in other users' interaction with the system (or even additional historical travel data) to come up with items for recommendation. From a user-only standpoint, we explore how comfortable users are when this data is used for better recommendations for other users, and then extend the concept to other stakeholders. In most interactive recommendation use-cases, explicit data collection practices on the part of the recommender system itself will result in collection of latent data such as click rates, page views and other heuristics. Such metadata is usually used for purposes such as advertising, monetisation, site improvements and so on. This data can also be used in a multistakeholder recommendation environment to benefit (directly and otherwise) stakeholders other than the user. This question aims to explore the users' willingness to be part of such practices.

4.3 Perceived Impact of Non-Functional Influences

With the final three questions of the study, we explore the effects of the concept of non-functional influences for multistakeholder recommender systems that we have defined earlier. It can reasonably be expected that owing to the nature of tourism as a whole, the users of tourist recommender systems will similarly be sensitive to effects from outside influences. Specifically, it can be assumed that when it is perceived by the users that there exist external changes affecting their preferred travel destination for a particular planned trip, they invariably try to either learn more about the impact or plan to work around it. For example, when the local law prohibits certain kinds of accommodation (such as Case 3 in our generated recommendations, where the city is assumed to forbid stays within hotspots), tourists may wish to be informed of local regulations surrounding their stay, and a recommender system is a perfect candidate to play this role as the sole system they will be interacting with. Conversely, when a high season starts, tourists would be more inclined to find cheaper accommodation even if it means their rental is slightly father away (i.e. effects from seasonal predictable influences). Here, a recommender system will be well placed to use such factors to the advantage of all stakeholders by balancing user utility in recommending suitable places as well as provider utility in recommending items that are not otherwise seen as desirable. Thus, we aim to view from the users' standpoint what they believe a tourism recommender system should do when such cases arise.

The questions posed in this part utilise the same 1 - 5 rating scale as the previous section.

4.3.1 I want recommender systems to take care of local restrictions when planning travel (e.g. if local law prohibits stays longer than 5 days, such choices must not be shown): through this question, we look at the users' view when constant external influences play a role in a multistakeholder recommender system for tourism. As we have seen, constant influences arising from outside the sphere of recommendation are common in tourism, mainly in the form of laws, statutes and other such restrictions. In these cases, the response trend could shed light into the share of recommender system users who wish to be informed of such restrictions by their travel recommender system. This data can also be useful in designing holistic recommender systems exclusively focusing on tourism and itinerary planning, such Inspirock[3], which usually need to account for such changes.

4.3.2 I am comfortable with tourist recommender systems taking care of changes coming from seasonal factors (like price drops), rather than do it manually myself: next, we consider the case of recurrent influences (both deterministic and non-deterministic) which impact tourism recommendation, such as touristic seasons. These changes are also good candidates to be incorporated into the recommendation process since they are periodic and usually affect touristic aspects, similar to constant influences as seen in the last question. this is especially true in the case of multistakeholder tourism recommender systems, where as we have already seen, there are good opportunities for utility improvement for stakeholders if such recurrent events are addressed in a suitable way.

4.3.3 I want tourist recommender systems to warn me when there are unforeseen events happening in my destination (e.g. pandemic, war): finally, we study the users' views on the the role played by volatile (and by nature non-deterministic) influences in tourism recommendations. Such effects are mostly entropic and may occur without obvious triggers or causes, making prediction and proactive response difficult. Therefore, understanding users' views on how a recommender system should handle such influences, even at a minimum start by telling the users about the occurrence of such events, will be greatly beneficial to stakeholders. Users benefit by having information (or sources for more information) at the very start, while providers, society and system all benefit by increased user awareness. For example, in the case of the COVID-19 pandemic, travel advisories were issued by many online tourism recommenders during the time of vacation bookings, resulting in greater user awareness as well as easier response on the part of local health authorities as a result.

5 RESULTS

The questionnaire was distributed online, through forums, message boards and social media posts. This enabled us to keep the user demographic as diverse as possible; and since no personally identifiable information was collected from the respondents, we do not consider user bias explicitly. At the end of data collection we obtained a total of 101 responses.

5.1 Reranking Recommendations

The aggregated results of this part of the experiment is presented in Figure 2.

As we have envisioned, the first iteration of reranking which closely matched the users' requirements of closeness to the city centre, low price per head and good ratings received positive responses, with over 64% of the surveyed users viewing the recommendation as positive. The word clouds from their remarks contained phrases such as "ratings", "matches", "close", "distance" and "price", reflecting the reasons for the high satisfaction.

[3] http://inspirock.com

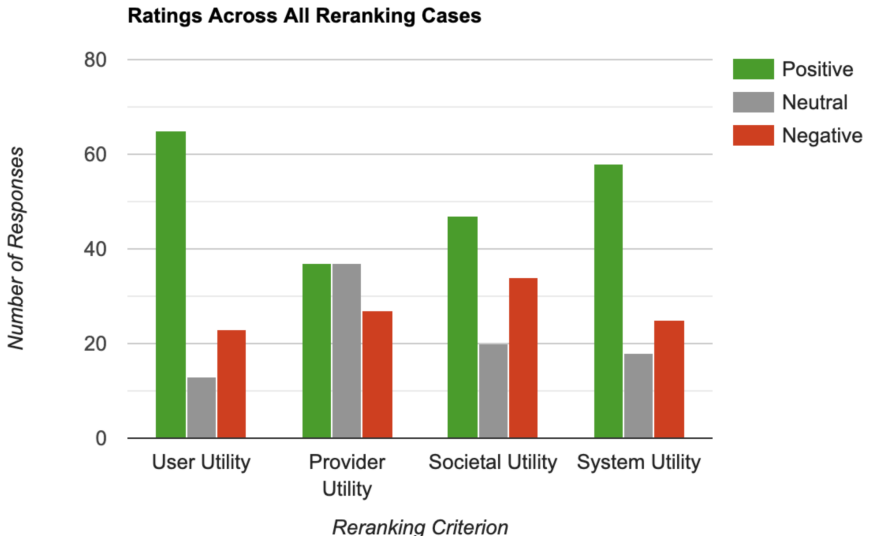

Fig. 2. Results of user satisfaction ratings across all reranking criteria.

In the second case where we prioritised providers' utility over others, the approval fell drastically to less than 40% of the users viewing the responses viewing the recommendation positively. As the listings were pricier to book compared to the previous case, the overarching sentiments reflected in the word cloud were "expensive" and "prices". This reranking also provided the most number of participants neutral about the result, a number which equalled the positive view of roughly 37%.

In the third case, where we simulate a gain in the city's utility by barring bookings in touristic hotspots in the centre, the listings recommended were cheaper but farther away from the centre. However, the respondents largely found this compromise acceptable, with higher positive responses of 46%. There were also more negative responses than the previous two cases, pointing to a polarising result. We also find the phrases "price", "far" and "good" in the word cloud, confirming this trend.

In the final case, which showed the users the most booked places which simulated a focus on system utility, we find that this is the second most positively viewed result, with an approval rating slightly below 60%.

Considering the distribution of positive and negative feedback, the trends allow us to conclude that users are sensitive to their utilities being affected by both other stakeholders in a multistakeholder recommender system. Even though not explicitly told when and how their original requirement is being swayed by the interest of other parties, users were able to gauge the impact of such effects and react accordingly.

5.2 Multistakeholder Travel Recommender Systems from the Users' Perspective

Table 2 summarises the results of the questions we had posed to the users to gauge their opinions on various aspects of multistakeholder travel recommender systems.

Even though only 57.4% of the surveyed participants have said that they explicitly prefer interactive recommender systems over other sources when planning travel, a large percentage of users (73.3%) display acceptance that their results are affected by other stakeholders' utility gains. Moreover, 84 users (83.1%) have also expressed their willingness to let

Table 2. Summary of user views of multistakeholder aspects

Question (abridged)	Agreement	Neutral	Disagreement
I prefer to use recommender systems for tourism.	58	26	17
Sometimes my results can be affected by other factors.	74	18	9
Recommender systems should prioritise my needs.	76	13	12
I should know when other parties' interests are affecting my results.	82	14	5
My data can be used to benefit other parties.	84	9	8

their data that was provided for recommendation purposes be used to benefit other users as well as other stakeholders of the recommender system.

On the other hand, as seen in the responses for the third and fourth questions, users also believe that the primary purpose of a recommender system that is used by them for travel recommendations is to serve their own needs, which is a clear indication that classical recommender systems should not change their core characteristic (taking the users' utility as the top aim), when they are made multistakeholder-aware. Users also demand more control and transparency during the recommendation process, with 81.2% of users stating that they need to know when other parties' interests are taken into account which might affect the results they may see.

Overall, it is evident that most users are aware of multistakeholder considerations affecting their recommendations, and are of the opinion that they need to be in control of the process.

5.3 Non-Functional Influences

From the results for the final part of the questionnaire, users are of the opinion that they wish the recommender system to help handle the impact of the non-functional influences on their trips. Figure 3 summarises these results.

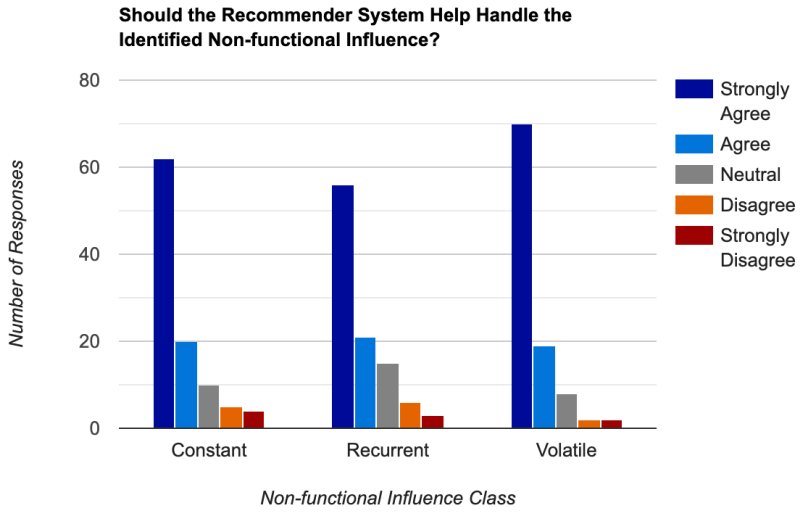

Fig. 3. User views on non-functional influences.

Users are especially expectant that in the case of volatile influences, the recommender system should inform them that there exists an unforeseen event in their planned travel location, with an overall positive vote from 78.1% of users. Even in the other cases, the agreement percentage is above 75% across the board. This means that as a start, recommender system architects could study the approaches in which this may be achieved, such as through incorporation of additional data sources to better inform the recommender system of these influences. Additionally, recommender system operators could use this result as a starting point in studying possible user-focused improvements to existing platforms.

6 CONCLUSIONS AND FUTURE OUTLOOK

Interactive tourism recommendation is an area that is set to experience tremendous growth in the near future, when the world slowly returns to normal following months of lockdowns and travel restrictions and where there is a huge number of tourists expecting to pick up things where they were left off. It would therefore make perfect sense to formally consider tourism recommenders from the lens of stakeholder-awareness to build even better systems offering more accurate recommendations. An added advantage would be a future where external, non-functional influences on the recommendation process are also studied as well as implemented in practical applications.

Through a user study, we have explored the perceived impact of other parties in a tourism recommendation scenario from the users' perspective; and we find that as the core focus of the recommendation shifts from users to other stakeholders, the users are reactive to the changes and view the end results positively or negatively depending on how their aims are affected. We also see that users are willing to acknowledge benefit to other parties as long as their core requirements from the recommendation process are upheld and the reasons for the focus shifts are made clear. Users are also of the opinion that the impact of external, non-functional influences should be handled with the aid of the recommender system. As a whole, a key takeaway from the study is that viewing tourism recommenders as multistakeholder environments is a worthwhile exercise, but one that requires care from the system designer such that parties are not unduly affected by factors from both within and outside the recommendation environment.

A potential challenge in incorporating the awareness of such non-functional influences into tourism recommender systems that are stakeholder-aware would be the lack of existing foundations to base responses and mitigation strategies upon. On one hand, the research done in this area is extremely light, while on the other hand, the data that would be needed to back such studies in the future are also sporadic and too heterogeneous. In other words, if a future study were to focus on the mitigation strategies in tourism recommenders against outside influences, the existing data that may be required to measure and evaluate the concepts are either spread out over many different systems or difficult to find. Hence, a good first step would be collating the data to a suitable format and processing it to benefit future uses.

The concepts introduced in this work could be further explored in future studies with added focus on related aspects, such as respondent demographics, user bias, recommendation fairness and so on.

Another interesting future direction includes a formal data-driven exploration of multistakeholder recommender system development in other areas peripheral to tourism such as transport; although similar to tourism use-cases the problem of acquiring suitable multistakeholder data for study is still a challenge.

A APPENDIX: ADDITIONAL RESOURCES

A collection of resources relevant to this work including additional figures from the results of the user study may be found at `https://gokul.github.io/msr-tourism`.

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