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Characterizing user behavior in journey planning

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Abstract Journey planners support users in the organization of their trips, by presenting them results with multimodal solutions. While the benefits for the users are straightforward, other stakeholders (such as transport operators and planners) might benefit from understanding how users behave. In this paper, we analyze and characterize user behavior in journey planners, with the aim of getting insights from different perspectives (namely, trip search and both sorting and selection actions related to trip options). Our results show that, in order to characterize user behavior, multiple perspectives have to be taken into account, and that users speaking different languages behave differently.

Keywords User behavior · Journey planners · Data Analytics · Transport

1 Introduction

The last 20 years have brought great changes in the way people travel and, accordingly, how they plan their mobility. On the one hand, flight costs have reduced significantly, and this increased the frequency with which we travel[1]. On the other hand, the use of the Web has increased, both in terms of more powerful Internet connections and of new devices thanks to which we access to it [12]. This has enabled, among others, an almost real-time planning of the most suitable routes. In the urban context, the variety of travel options is richer than ever and includes for example smartphone-based ride sharing

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[1] https://ec.europa.eu/transport/sites/transport/files/2016_eu_air_transport_industry_analyses_report.pdf

(e.g., Uber, BlaBlaCar) and micro-mobility. The mobility ecosystem is evolving towards an open and integrated transport system, summarised by the concepts of Mobility as a Service (MaaS) and open transport data [7]. From the end user perspective, journey planners shall address the requirement of supporting door-to-door multi-modal trips combining public and private transport offer.

In this scenario, Web tools have become key for the users to plan their travels and filter the vast amount of opportunities they have in terms of transport providers and means of transport. Journey planners allow users to organize a trip[2], navigating among the vast amount of different options they have to go from a point A to a point B [8,5,26]. More specifically, given a query composed by departure location, arrival location[3], and date and time of the inbound (and outbound) trip, a journey planner returns multimodal results, which contain the different available options to make that trip, both in terms of modes of transports and companies that allow the user to complete a given trip leg. In addition to that, each multimodal result usually contains aggregate information that can help a user get a high-level overview of each trip option (e.g., total price, time needed to complete that trip, emissions, etc.) [26]. As in all the decision support systems, additional tools such as a ranking of the results personalized on their preferences might be available to the logged in users [13].

In this work, we analyze data coming from an international journey planner service, named *RouteRANK*[4]. This study is done in the context of the Horizon 2020 project *MoTiV (Mobility and Time Value)*[5], whose goal is to provide novel definitions of value of travel time [14,16,18]. In the MoTiV context, value of travel time is analyzed from a traveller's perspective, assuming that time and cost savings are not always the main criteria influencing route and mode choice. Depending on the traveller's transport attitude and context, other criteria such as environmental impact, comfort or even weather conditions may influence the perceived value of a trip. To some extent, route planners already take into account some of these aspects as criteria for customizing the available travel options. In the near future, optimising the use of one's time while traveling (i.e., maximising perceived value during the trip) may become as important as reducing travel duration or cost. In MoTiV, one of the aims is to provide a traveller-based 'worthwhileness index' for each trip, which may represent the default criterion for sorting travel options. Hence, the need for further research into end user behavior in travel planning based on actual travel choices as those from the RouteRANK journey planner, which are considered in this article.

Specifically, we characterize user behavior from three main perspectives:

Search behavior. This perspective allows us to study what the users look for and the behavior associated to it (e.g., the type of journeys that are searched and spatio-temporal aspects associated to journey planning);

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[2] In this paper, we will use the terms "journey" and "trip" interchangeably.

[3] Both departure and arrival locations can be constituted of a specific address, thus indicating a door-to-door trip.

[4] https://www.routerank.com

[5] https://motivproject.eu/

Sorting behavior. When a user sorts the resulting trip options according to a specific property of the results (e.g., the carbon emissions or the price); this gives us insights on the relative importance of criteria shaping users' expectation in terms of value of travel time for a specific trip, thus influencing the final travel option choice;

Selection behavior. Given the result selected by a user, we inspect combination of criteria associated to the selected travel option.

Of course, when talking about user behavior, it is impossible to create this separation between the different aspects that are part of the user experience in a journey planner (i.e., search, sort, and journey selection), and we are aware that one aspect influences the others. For this reason, we will also try to analyze the interaction among these perspectives in joint analyses, to consider how the experience of a user inside a journey planner evolves during a search session (e.g., to check if the characteristics of the journey a user finally selects, actually reflect the criterion that she chose to rank the results).

Data coming from journey planners was previously used to analyze user behavior, to consider aspects such as their willingness to pay for services [28] and challenges in behavior change [24]. When a characterization of user habits is performed, similarly to our work, the focus is on a specific city (Budapest) [15]. Manca et al. [19] presented a survey on mobility patterns considering social media data. González et al. [10], instead, consider mobile phone data, while Calabrese et al. [3] extract mobility patterns from urban sensing data.

Goulias [11] surveyed the existing travel behavior models. Data analysis has been performed to analyze data coming from a travel agency [23], to characterize mobility styles and travel behavior [17], to study the influencing factors of check-in time in air transportation [21], to assess the willingness to pay for the use of multimodal journey planning systems [28], to characterize user habits and multimodal route planning in Budapest [15] or to consider the challenges in behavior change by using data coming from a journey planner application [24]. Data analysis can produce insights that serve as input for other purposes, such as the improvement of transport services by considering user needs [25], the promotion of changes of the user habits [24], and the improvement of journey planners and transport portals [9,27].

This is the first time that user behavior in journey planners is characterized with an international user base, considering several factors and perspectives.

The contributions of this research work can be summarized as follows:

- We are performing, for the first time in the literature, an analysis of the user behavior in a real-world journey planner (RouteRANK);
- This is the first study of multiple factors affecting user behavior (i.e., search, sorting, and selection), considering users from several countries;
- This work provides results that can benefit the research community working on user behavior in transport system. The approach we developed attempts to directly explain user behavior in journey planning from the viewpoint of perceived value of travel time. This approach will be further developed in the MoTiV project (more details are given in Section 9), to introduce a novel methodology for estimating value of travel time from the trav-

eller's perspective. This methodology will have practical implications for the design and improvement of transport infrastructures and services.

2 Dataset

As previously mentioned, the analyzed dataset is provided by the international journey planner service RouteRANK. It is Web-based mobility solution addressing the entire door-to-door route by integrating all relevant modes of transport and their many multimodal combinations. Routes can be sorted according to multiple criteria, such as price, travel time, and CO2 emissions.

When a user performs a search in the system for a travel from a source location A to a destination point B, the system retrieves a set of possible journeys for that search. Each journey is composed by one or more legs (segments). The user can sort the results retrieved by the journey planner based on different criteria and select one or more results.

More formally, we are given a set of n searches $S = \{s_i\}_{i=1}^{n}$. Each search s_i is a tuple $s_i = (q_i, r_i, F_i)$, where:

- $q_i = (source_i, destination_i, inbound\_date_i, outbound\_date_i)$ indicates the query made by the user in the system;
- $r_i = \{j_i\}_{i=0}^{m}$ is a set of query results, where a journey $j_i = \{l_k\}_{k=1}^{t}$ is composed by a set of legs (also called segments);
- $F_i \subset F = \{Arrival, Departure, Duration, Emission, Price, Rank, Via\}$ is the set of criteria that the user used to sort the results.

Each journey j_i is described by the following characteristics: Duration, Price, Vias (number of stopovers) and CO2 (in ppm). Each segment of a journey is identified by the following features: Duration, Price, Arrival Time, Arrival Date, Departure Date, Departure Time, Means of Transport, CO2 (in ppm), Origin and Destination (in latitude and longitude). In addition to this, we compute for each journey the departure time of the first segment of the journey and the arrival time of the last segment of the journey.

Table 3 summarizes the main characteristics of the analyzed dataset, which has been collected during a six-month period, from September 26, 2018 to March 15, 2019 and is GDPR-compliant (no personal information is available).

3 Characterizing search behavior

In this section, we characterize the search behavior of the users. In order to do so, we pose two main research questions:

RQ1. What kind of trips do users look for when planning their journeys?

RQ2. Does the language of the users (that is used as a proxy for their origin) allow us to characterize the type of search behavior, in terms of distance covered in the journeys and temporal gap between search and travel time?

Total n. of searches	17982
N. of searches that retrieve at least one journey	11295
N. of searches that do not retrieve any journey	6057
N. of journeys	472249
N. of selected journeys	3548
Average n. of journeys per search (all searches)	26.26
Average n. of journeys per search (only searches w/ journeys)	39.60
Average n. of segments per journey	2.70

Table 1 Dataset description

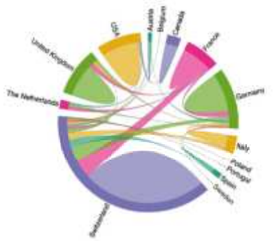

Fig. 1 Connection between departure and arrival countries in searches.

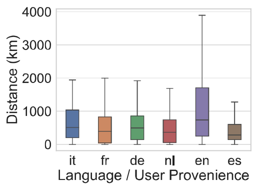

Fig. 2 Distance covered by the users, according to their language in the platform.

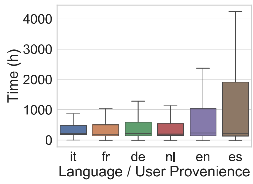

Fig. 3 Number of hours between search and travel time, based on the language.

Factor	**Sorts**
Price	656 (34.8%)
Duration	533 (28.28%)
CO2	400 (21.22%)
Rank	153 (8.12%)
Departure	88 (4.67%)
Arrival	35 (1.85%)
VIA	20 (1.06%)

Table 2 Relevance of the sorting factors.

Searched countries analysis. In order to characterize the types of trips searched by users, we considered each departure-destination pair, and counted their frequency. To be able to analyze the results, we considered only the top-35 most frequent searches (which correspond to pairs appearing at least 30 times).

Figure 1 presents the results in a chord diagram. The circumference arc associated to each country indicates its relevance in the searches. Two countries are associated by an internal edge, whose thickness indicates the frequency with which the pair appears; the color of the edge is that of the origin country. Results show us that the journey planner was mostly used by Swiss users, mostly to make internal journeys (indeed, there is a very thick blue edge). Internal journeys are also very frequent for the other countries. Besides internal journeys, Switzerland is also the main destination in the searches. Its popularity is clearly due to the fact that RouteRANK is a Swiss portal. Another interesting phenomenon is that neighboring countries are usually searched together (e.g., France-Switzerland, Canada-USA, and France-Germany).

Characterizing search behavior by user provenience. In order to characterize how the provenience of the users impacts the types of journey they look for, we used the language as a proxy of the country of origin (studies have shown that users prefer to browse a website according to their native language [4]). This was the most suitable indicator, in absence of personal data in the dataset.

Figure 2 presents a boxplot for each language, characterizing the distance covered in the searches. Results show that, independently of their origin, users search mainly for long-distance trips (i.e., beyond the urban context). English-speaking users[6] are the ones who look for higher distances. Italian-, French-, Deutsch-, and Dutch-speaking users show similar behaviors. Spanish-speaking users, instead, cover a lower range, so the median distance is also lower.

Figure 3 shows that, independently of provenience, users do not use journey planners for real-time planning but rather plan trips a few days or even weeks in advance. Spanish users are the ones with the highest gap between search and travel time. The users speaking the first four languages confirm to have a similar behavior. We can also see that the Spanish-speaking users have a planning behavior that leads them to organize journeys much in advance, despite the covered distance. The results related to English confirm that distance is correlated with the temporal span between search and departure date.

4 Characterizing sorting behavior

The sorting behavior of the users allows us to understand what are the aspects that are important for them when assessing trip options. With this analysis, we aim at answering the following research questions.

RQ3. Which travel option optimization criterion seems more relevant to users, based on their sorting behavior?

RQ4. When users sort multiple times, is there any recurrent pattern?

Relevance of the sorting criteria analysis. In order to understand the relevance of each factor in the sorting behavior of the users, we count the number of times the users sorted by that factor (in case a user in a search sorts the results multiple times, we count all the factors for which she sorts). As Table 2 shows, while price and duration are clearly (and not surprisingly) dominant factors, the carbon emissions of the journey (CO2) are also an important criteria, indicating an attention of the users that goes beyond time and cost savings. "Rank", i.e., the factor that puts together the others, indicating the ideal ranking according to the platform, is considered much less, thus showing that users want clear control over the way results are shown. Arrival and departure times and the number of vias do not matter much when sorting the results.

Correlation between subsequent sorting factors. In order to answer RQ4 and understand if there are recurring patterns in case of subsequent sorts in a single search, we mine association rules [1]. We consider the set F of user factors in terms of sorting behavior and each single action of the users as a transaction.

By performing Association Rules mining, we aim at discovering classification rules that explain the co-occurrence of the sorting behaviors. In addition, association rules can be exploited to build a recommender system [6]. Indeed, classical recommendation approaches need detailed user or item profiles and a significant amount of historical data that is usually not present in a journey planner. This limitation can be addressed by building a recommender system based on a set of pre-computed association rules [22]. In this case, based on

[6] With this term, we refer to those who select English in the RouteRANK platform.

the first sort of the user, the system would predict the next sorting preferences and retrieve a ranked list of journeys. The parameters *support*, *confidence*, and *lift* control the rules that are generated. *Lift* can be considered as a function similar to statistical significance testing in more traditional analyses [2].

To perform the mining, we used the Python library mlxtend, choosing as parameters $support > 0.03$, $confidence > 0.03$, $lift > 1$. The obtained results are the following: (1) $\{Rank\} \rightarrow \{Duration\}$; (2) $\{Rank\} \rightarrow \{CO2\}$; (3) $\{Price, Duration\} \rightarrow \{CO2\}$; (4) $\{CO2, Price\} \rightarrow \{Duration\}$; (5) $\{CO2, Rank\} \rightarrow \{Duration\}$; (6) $\{CO2, Duration\} \rightarrow \{Rank\}$; (7) $\{Rank, Duration\} \rightarrow \{CO2\}$; (8) $\{Price, Rank\} \rightarrow \{Duration\}$; (9) $\{Rank, Duration\} \rightarrow \{Price\}$.

As the rules show, if a user sorts by rank first and by duration later, she either sorts by CO2 (rule 7) or by price (rule 9). When sorting by CO2, people usually do a second and third sorting (rules 4, 5, and 6). In addition to that, there are factors that are never part of recurring patterns in the sorting behavior of the users (i.e., Arrival, Departure, and via). Indeed, as Table 2 shows, they are not frequent factors, and thus are not part of any pattern.

5 Characterizing selection behavior

After analyzing search results, a user can finally select the travel option that most suits her needs, based on the most suitable combination of criteria. Here, we analyze the selection behavior, considering the following question:

RQ5. Does the provenience of the users impact the type of results they select?

In Fig. 4, we characterize the carbon emissions of the users, according to the journey they selected and their language. Italian-speaking users, even though they are not the ones making the longest journeys according to Fig. 2, are the ones with the highest median in terms of carbon emissions. English-speaking users, being the ones with the longest journeys in terms of distance, are the ones with the highest covered range of emissions. Even though we previously saw that Spanish-speaking users are the ones who cover the lowest distances in their journeys, their emissions are aligned with those of Italian- and English-speaking users. One trend that emerges is that the carbon emissions do not seem to correlate to the covered distance; indeed, no language shows a similar behavior, while this happened when we considered the distance in the searches.

Next, we analyze together two phenomena, by presenting the duration of the selected journeys (Fig. 5) and their price (Fig. 6). Results show that the two factors have the same trend. The main difference is related to the Dutch-speaking users (*nl* boxplot), who manage to make journeys with duration similar to the French- and English-speaking ones, but spending much less.

In a summary, Italian-speaking users are the ones whose selected journeys have the highest emissions (CO2), price, and duration; while the association between these three factors is trivial (cars have high emissions, fueling has a high price, and cars are slower than trains and planes), a possible reason behind this behavior is the comfort coming from a private means of transport. English-, Spanish-, and French-speaking users show a similar behavior and

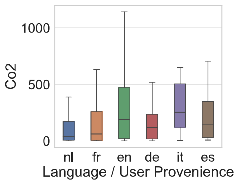

Fig. 4 Estimated emissions by users, according to the language used in the platform.

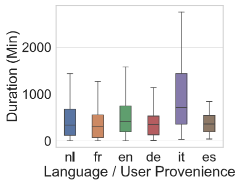

Fig. 5 Travel duration, considering the language used by the users in the platform.

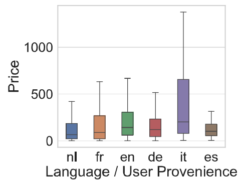

Fig. 6 Budget spent per travel, considering the language of the users in the platform.

this is true also for Deutsch-speaking users, except the lower emissions. The Dutch-speaking users stand out for their greener and money-saving journeys.

6 Characterizing sorting and selection behavior

In Sections 4 and 5, we studied respectively the sorting and selection behavior of the users. The current section analyzes if there is a correspondence between the intent and the choices of the users, by doing a cross analysis between the sorting and the selection behavior. Summarizing, in this section we aim at providing an answer to the following research question:

RQ6. Is there a real correspondence between the initial intent of the users and their actual behavior?

To perform this analysis, we filter all the searches containing at least one selected journey. For each selected journey in a search, we infer the criteria used for its choice by analyzing if it was the cheapest, the shortest in terms of time, the first in terms of arrival or departure time, number of stopovers (vias) and/or the first following the RouteRANK ranking. Notice that a given journey may not reflect any of these criteria or may also reflect multiple ones (e.g., a journey can be the cheapest and shortest one at the same time). From the obtained set of searches we filter out those that do not match any selecting criteria and, then, the resulting set of searches is intersected with the set of searches where the users performed at least one sorting action. The result of the above process is a dataset composed of 282 searches where 103 do not share sorting and selecting behavior, 158 share one common sorting and selecting behavior, 20 share two common sorting and selection behaviors and 1 shares three common sorting and selecting behaviors (*Price*, *Emission*, *Duration*).

Figure 7 shows the number of searches that were sorted based on a criterion and then selected following a different one[7]. Fig. 8 reports, for each sorting and

[7] Note that the sum of the elements is not 103 because the same journey can be sorted and selected by multiple (not corresponding) criteria. For instance, a search s_1 may be sorted by (*Price*, *Duration*), while the selected journey is the one with lowest (*departureTime*, *arrivalTime*). In this case this single journey will appear four times in the plot, as: *Price-departureTime*, *Price-arrivalTime*, *duration-departureTime* and *duration-arrivalTime*.

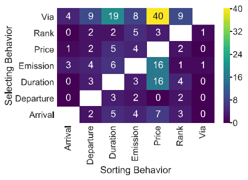

Fig. 7 Searches that do not share sorting and selecting behavior.

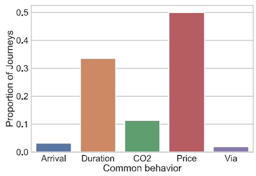

Fig. 8 Searches that share one common sorting and selecting behavior.

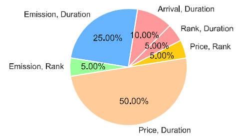

Fig. 9 Searches that share two common sorting and selecting behaviors.

Table 3 Cluster centroids

Cluster	CO2	Duration	Price	Distance	Gap
Cluster 1	496.59	44329.25	282.21	1612	3834.16
Cluster 2	140.24	19641.31	124.58	525.58	366.69
Cluster 3	2352.80	100272.92	949.19	8233.63	1491.47

selection criterion, the proportion of searches that share it. In Fig. 9, we show the percentage of searches that share two sorting and selection behaviors. Our results highlight some consistency between the intent and the choices made by users. Indeed, in Table 2 *Price* and *Duration* appear as factors for the users and Figs. 8 and 9 confirm this. Hence, classic definitions of value of travel time, focusing on time and cost savings, are a strong component in travel planning.

7 Traveller segmentation

Here, we analyze user behavior through a traveller segmentation. Precisely, we analyze which aspects are more relevant for the users during the search and the selection phases. To this end, we generate a new dataset with searches that contain selected journeys. For each search, we consider the distance between source and destination, the difference in hours between search and travel time, and we compute the average price, emissions, and duration of its journeys. The dataset contains 1996 items with the following features: *CO2* (in ppm), *Duration* (in seconds), *Price* (in Euros), *Dist* (in kms), *Gap* between search and travel time (in hours). Being the variables of incomparable units and in different ranges, we perform a pre-processing through a *z-score* standardization, which is widely used in clustering tasks [20]. The standardized data is then used to feed the *K-Means* clustering algorithm, implemented in the sklearn Python library. The number of clusters that better segments the users is 3. Table 3 reports the centroid of each cluster, which have the following profiles:

1. Users that perform short journeys (as a consequence with low emissions, price, and duration) and reserve with little advance.
2. Users that perform short-medium distances, but reserve much in advance.
3. Users that, although the journey is a long and expensive one, do not schedule it much time in advance. This profile of users is constitute by those who also pay less attention to the environmental aspects.

8 Discussion

In this section, we aim at discussing the results, by providing take-home messages, which try to connect the insights coming from the individual analyses.

In the age of increasingly integrated and open transport systems, journey planners represent an important tool for travellers, who wish to identify the most suitable travel option meeting their expectation of value associated to a specific trip. Due to the highly subjective and contextual nature of this process, journey planners do not only need to provide a wide range of multimodal and door-to-door travel options, but also an increasingly high number of criteria for further processing such options to identify the most suitable one for a trip. For the same traveller, the criteria of choice for a travel option may significantly differ depending on the trip purpose, travel distance or types of meaningful activities that can be carried out during the trip. These can be broadly associated to the comfort criterion and premium services such as the provision of high-speed Wi-fi in the 1st class of long-distance trains or coaches. In this respect, an in-depth understanding of travellers behavior in journey planning is functional to identify the type of information and criteria that it would be beneficial to include in journey planners for better meeting travellers needs. The analysis performed in this article, even with some limitations due to the nature of the dataset, indicates that investigating users' travel behavior through criteria like search and sorting may already provide valuable insights, especially when crossing multiple perspectives (as done in Sections 6, 7).

A clear example is "via", which is hardly used as a sorting factor and does not appear in any association rules, but emerged as the main one in the selection process (Fig. 7 shows this phenomenon). In other cases, the additional analyses confirm the results already obtained. This is the case of Arrival and Departure as sorting factors which, when considered individually, are not very relevant and indeed, they do not appear in any pattern detected through the association rules. Although Fig. 1 highlights that most of travels done by English and American people are internal, in Fig. 2 we observe that the travels performed by English speakers are the longest ones in terms of distance. This may be due to the presence of some cross-country travel from the USA to United Kingdom and to the considerable geographical sizes of the USA.

9 Conclusions and Future Work

In this paper, we characterized user behavior, by analyzing the search, sorting, and selection perspectives. More specifically, we analyzed how segments of users speaking different languages behave and highlighted differences from that perspective. Moreover, we connected different perspectives and showed how the behavior of the users changes during their journey planning experience.

Current limitations of this study are related to the lack of personal information about the users, which did not allow us to profile them and analyze perspectives such as the gender, the age, personal preferences and lifestyle.

Another important factor to characterize user travel behavior is the *attitude* of the users towards traveling, with perspectives such as why they are making the journey and the possibility to monitor user behavior after the planning activities (e.g., during travel time, to collect information on their mood).

In order to overcome these limitations, future work will be focused on the analysis of a richer dataset collected in several European countries through the Woorti mobile application[8], developed in the MoTiV project. This dataset, which will be published as an open dataset, will allow us to identify factors influencing the perception of time value in multi-modal trips, thanks to information on the perceived worthwhileness of a trip leg, activities carried out during a trip and positive or negative assessment of transport infrastructure and services or other contextual elements (e.g., weather). Associations among such factors will be studied across travellers' socio-demographics and attitudes.

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