Modelling tourist on-site mode choice decisions during vacation stays

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1. Introduction

In popular and highly frequented tourist regions, local authorities and Destination Management Organizations struggle with providing high level of service on a restricted road network used not only by local daily and leisure traffic but also by an extensive seasonal tourist traffic. So far, they operate with limited knowledge since the data on how tourists travel on-site at the vacation destination, albeit crucial for local transport policies, is unknown. It is not covered by typical household travel surveys nor have any models been developed for the local travel of tourists yet. Also current research is limited and concentrates merely on international tourism demand and long-distance trips (Axhausen and Janzen, 2018; Christensen and Nielsen, 2018; Gerike and Schulz, 2018).

The main goal of the study is to create models reconstructing the on-site mobility behavior of tourists at the destinations during vacation stays. It is motivated by the fact that this behavior may be very different from the daily travel behavior at home and also different from the behavior of local residents of the destinations. According to our knowledge, this research is a first attempt to close this gap. We tested various specifications of discrete choice models and identified factors influencing the mode choice decisions of tourists. Based on that, we briefly outline policy change recommendations.

2. Methodology

The data used comes from an extensive survey on the mobility behavior of tourists that was conducted in three tourist regions in the Austrian Alps in both winter and summer high season. The survey collected sociodemographic characteristics, sojourn information and travel data using a travel-activity diary for two days. This is one of very few applications of the travel diary-based survey approach for the intra-destination mobility of tourists (Bursa and Mailer, in press).

Overall, data on 4164 trips were collected. A very complex data cleaning process resulted in 2360 valid trips (994 in winter and 1366 in summer). In the case of trips made with slow modes, in particular in summer when the outdoor activities are more varied, the classification of the walking and cycling movements either as an activity or as a trip presents difficulties. A precise differentiation between these two requires often a lot of manual interpretation and considering the daily schedule and context of the individual. The attributes of the alternatives (travel time and cost) were generated with the use of GoogleMaps API (Cooley, 2018; Kahle and Wickham, 2013) for driving, walking and cycling and the regional VISUM transportation model for transit.

We employed the random utility modeling techniques. Various specifications of the Multinomial Logit Model (MNL) (Ben-Akiva and Lerman, 1985) were estimated with the use of the Apollo choice modeling package (Hess and Palma, 2019) in R statistical software (R Core Team, 2019). For modelling purposes, the alternative modes were aggregated into four groups – "car" comprising private and rented car/motorcycle both as a driver and as a passenger, "transit" covering bus and train modes, "cycling" consisting of bicycle and e-bike and "walking".

So far, the models operate on the level of trips; however, trip chaining is indirectly accounted for through availability constraints, so that the choice set differs for every individual and every choice situation during the tour. We want to highlight the importance of the calculation precision of mode availabilities and travel costs, which is often ignored or not reported by researchers. Various region-specific offers must be taken into consideration in the cost calculation, e.g. free transit for visitors during their stay (only for trips within a certain area or time range), transit tickets included in some (paid or unpaid) visitor cards, bicycles rented or offered free-of-charge at the hotel, etc.

3. Results

The values of intercepts indicate a higher initial preference for walking at the destination compared to car and lower for transit. The coefficients of the key predictors: travel time and cost have negative signs as expected and are significantly different from zero. The magnitude of these effects is independent from age, gender and income. For access/egress to/from bus stop, walking time rather than distance was used as it takes into account the altitude difference, which is often considerable in the alpine topography.

Apart from the above mentioned we tested other factors suggested in the literature. We found for example that better knowledge about the mobility at the destination has a favorable effect for the use of transit. Furthermore, the purpose of the trip plays a crucial role for the choice – an interesting finding is that the transit alternative is the preferred option to travel to sport activities (skiing, cycling, hiking, climbing, etc.) in both winter and summer season. The overall fitness level represented by the frequency of practicing sport activities at home has a positive effect on walking in winter and on cycling in summer (with positive elasticity regarding distance).

Weather conditions described by temperature, precipitation, wind and overcast proved not significant for choosing any of the alternatives in winter, however they have a negative impact on choosing cycling in summer, which confirms findings from studies on daily travel behavior (Liu et al., 2017). The size of the family/group has a negative effect on choosing walking and cycling in summer, which supports the arguments of Bieger and Laesser (2013) only to some extent as there is no significant effect on the use of transit. Neither length of stay nor the elapsed days of vacation were found significant in the models. Table 1 reports estimation results of the MNL model with the variables significant for winter dataset.

Table 1. Estimation results of the MNL model for winter data

Predictor	Estimate	Robust st. errors	Robust t-statistic	Signif. level
Walk (intercept)	1.7640	0.3045	5.7935	***
Transit (intercept)	-3.1817	0.9206	-3.4562	***
Travel time car	-0.1292	0.0784	-1.6480	**
Travel time walk	-0.1549	0.0276	-5.6204	***
Travel cost car	-1.1385	0.7819	-1.4562	
Travel cost transit	-1.0936	0.2329	-4.6947	***
Access time transit	-0.1095	0.0449	-2.4407	*
In-vehicle time transit	-0.1305	0.0456	-2.8599	**
Egress time transit	-0.1368	0.0564	-2.4235	*
Level (1-5) of information about on-site mobility (transit)	0.7130	0.1931	3.6933	***
Trip purpose == skiing (transit)	1.3136	0.2732	4.8087	***
Sport frequency (walk)	0.1332	0.0575	2.3177	*

Significance codes:	<0.001 ***; <0.01 **; <0.05 *
Number of individuals	219
Number of observations	994
LL(0)	-424.6835
LL(final)	-321.1101
R-squared	0.244

4. Conclusion

The work is probably the first attempt to analytically investigate factors influencing the transport mode choice of tourists for the intra-destination trips and provides foundation for evidence-based policy measures in tourist regions.

In terms of policy implications, the reluctance of families and groups to use slow modes in summer should be addressed, paying attention to the need of traveling with luggage. Better transit services in the evening, when other activities than sport dominate, are also desirable. Furthermore, we suggest concentrating on information campaigns as a better knowledge about transit options on-site significantly increases the willingness to use transit during vacation.

In terms of methodological findings, this research demonstrates the application of surveying and modeling methodology to study the transport mode choice of non-locals. It gives an overview of potential methodological and data-related difficulties one can come across. Due to limited literature on the determinants of mode choice at the destination , the character of this research is rather explorative. We argue that a broader set of potential predictors should be examined in a tourism travel context than in the daily mobility conditioned by work and leisure purposes.

So far, the models operate only on a trip level of single individuals. Since most visitors to alpine destinations are families and groups, it would be beneficial to model their joint decisions using group utility functions (Timmermans and Zhang, 2009). One must be also aware of a non-representative character of the sample. Tourists stay at the destinations in the Alps at most 1-2 weeks and are dispersed over a larger area, which makes the sampling process difficult to control. Another aspect is the quality of attributes of transport modes in non-urbanized areas generated from the external sources like GoogleMaps. It would be advised to compare the results with outcomes from alternative data sources.

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