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Article

Mode Choice of City Tourists: Discrete Choice Modeling Based on Survey Data from A Major German City

Jonas Harz[1*] and Carsten Sommer[2]

1 University of Kassel, Chair of Transportation Planning and Traffic Systems, Mönchebergstraße 7, 34125 Kassel, Germany
2 University of Kassel, Chair of Transportation Planning and Traffic Systems, Mönchebergstraße 7, 34125 Kassel, Germany
Correspondence: jonas.harz@uni-kassel.de

Abstract: With growing city tourism, there is an increasing need for urban travel demand models to consider traffic generated by visitors. Existing research has concentrated on socio-demographic and journey-related factors to determine what influences the mode choice of tourists. In contrast, revealed preference data, like travel time, is almost never considered. In this article, we present the results of discrete choice modeling of city tourists' mode choice based on revealed preference data from a survey we conducted in Kassel, Germany. We used multinomial logit models and determined the model parameters using maximum likelihood estimations. Surprisingly, travel time played a smaller role in mode choice than understood from previously established knowledge about everyday mobility. In the final model, travel time was only significant for the alternative walking. Also, most other sociodemographic and journey-related variables showed no significant influence. The final model reproduced the mode choice, but the goodness of fit was lower than expected from other research. We conclude that modeling the travel behavior of tourists is more complex than everyday mobility. An alternative approach that we suggest would be to model trip chains rather than single trips.

Keywords: discrete choice modeling; mode choice; travel behavior; city tourism; sustainable tourism; revealed preference data

1. Introduction

City tourism has experienced remarkable growth in recent years. Between 2014 and 2019, the market share of city trips in all journeys worldwide grew from 22 % to 30 % (IPK International, 2020, 2015). The increasing number of visitors in connection with the fact that tourism concentrates around certain areas of interest and time periods is leading to growing problems for cities (Gao et al., 2021). Furthermore, tourism has a considerable impact on greenhouse gas emissions, especially due to tourists' arrival and departure (Gühnemann et al., 2021), but also because of intra-destination trips if they are made by car. All this leads to the necessity for transportation planners to take tourism into consideration.

Travel demand models are an established instrument for forecasting transport and evaluating the impact of measures on current and future traffic networks. These models usually rely on structural and sociodemographic data of the model area and its inhabitants. The travel demand generated by visitors is rarely considered in these types of models resulting in the inability to evaluate the impact of measures that are geared towards tourists, like new public transportation lines to touristic hot spots. Some regional and state models, especially in areas where tourism is a large economical factor, include experimental approaches to consider visitors in their model for improving model quality. Examples of this are the transport model of the Swiss canton Graubünden (Arendt and Oswald, 2012) and a model extension of the Austrian state of Salzburg by Hofer et al. (2016). The missing integration of tourism in urban travel demand models is notable.

Existing approaches are often based on assumptions rather than empirical information and use existing mobility information from locals due to a lack of data on the travel behavior of tourists, especially during their stay. This so-called intra-destination traffic depends heavily on the definition of the destination. The destination may consist of a whole state, a touristic region, like an Alpine valley, or a smaller geographic entity, like a city, depending on the scope of different research. As a result, the length of trips varies and therefore the influencing factors on the mobility of tourists may be different. In this paper, we define the intra-destination traffic of tourists as any trips made by visitors between their arrival at and departure from the visited city, in our case the city of Kassel.

Visitors have to make a number of decisions during their stay. Initially, they must choose a sequence of activities resulting in their daily activity pattern. Furthermore, they choose a mode of travel and lastly routes to reach their destinations.

The mode choice models of conventional urban travel demand models usually rely on mode and also alternative specific variables, especially travel time and travel costs. The macroscopic nature of these models means that sociodemographic information is not part of the choice process but is usually considered using behaviorally homogeneous groups of the model population. . Several studies have indicated that variables like gender (Scheiner and Holz-Rau, 2012) and income (Jara-Díaz and Videla, 1989) have a large influence on individual mode choice.

Table 1. Literature review on the factors influencing the mode choice of tourists

Category	Variable	References
(1) Sociodemographic information	Age	GM, GG, MZ
	Car ownership	GG
	Driver's license	QZ
	Education level	GM
	Employment status	GG, QZ
	Gender	MZ
	Household structure (marital status/size)	GG, BS
	Income	GM, GG
	Origin of visitor	GG, MZ
(2) Journey-related factors	Familiarity with the destination	GM
	Group size	QZ, BM, LG
	Length of stay	GM
	Overnight/day visit	BS
	Type of trip	GG
(3) Motivation and information related factors	Drive-free benefit	LG
	Feeling safe and secure	MZ
	Lack/level of information	LG
	Meet new/local people	MZ, LG
	Personal preferences	LG
(4) Trip or mode related factors	Type of activity	BM

GM: Gutiérrez and Miravet (2016), GG: Gross and Grimm (2018), MZ: Masiero and Zoltan (2013), QZ: Qi et al. (2020), BS: Bieland et al. (2017), BM: Bursa et al. (2022), LG: Le-Klähn et al. (2014)

A key factor on the mode choice of intra-destination trips is the mode choice for the journey to the destination. If a person does not travel by car, he or she will in most cases have no access to a car at his or her holiday destination and will be forced to move around by public transport or on foot. This was shown by several studies, such as Gutiérrez and Miravet (2016)], Lew and McKercher (2006), Gross and Grimm (2018), and Bieland et al. (2016). The mode choice for the journey can be seen as analogous to mode availability variables in conventional travel demand models.

Further influencing factors can be grouped into four categories: (1) sociodemographic factors, (2) journey-related factors, (3) motivation and information related factors, and (4) trip or mode related factors. In Table 1, we summarize the findings of a literature review that concentrated on explaining and influencing factors for the mode choice of visitors.

In this article, we present the results of discrete mode choice modeling of city tourists based on revealed preference data from a survey we conducted in Kassel, Germany. The survey work and modeling is part of the research project "transport demand modeling of same-day visitors and tourists in cities," funded by the German Research Foundation (DFG), project number 409499825.

2. Methodology

2.1. Study area

The city of Kassel with its 200,000 inhabitants is the regional center of the north of the German federal state of Hesse. Due to its history as the former capital of the state of Hesse-Kassel, the city has a rich offering of parks and palaces as well as a comprehensive number of museums. The most notable park is the Bergpark Wilhelmshöhe, one of the largest landscape parks in Europe. With its extensive water features, the Bergpark was granted World Heritage status by UNESCO in 2013, resulting in a distinct increase in the number of visitors. Additionally, every five years Kassel hosts the documenta, an exhibition of contemporary art that is one of the largest and most important worldwide. It lasts for 100 days and attracted nearly 900,000 visitors from all over the world in 2017. Due to its central location within Germany and its very good rail connections, Kassel is a very popular choice for conferences and business meetings, resulting in a very good hotel infrastructure.

We chose Kassel as the study area for our research because of our good local knowledge and access to local and regional data from the city and tourism authority.

2.2. Survey work

It is common practice for cities and countries to gather data on the everyday travel behavior of their population. Surveys like "Mobility in Germany (MiD)" (Le-Klähn et al., 2014) and the Dutch travel survey OViN (Centraal Bureau voor de Statistiek, 2018) use the most prevalent approach of travel diaries. These are a special type of questionnaire that asks respondents to report on all trips they made in a specific period (often one day) including information like mode, duration, and purpose of the trip. Because these surveys usually aim at the travel behavior of the respective population, very little to no data on the inter-destination travel behavior of tourists is available. The concept of travel diaries has rarely been adapted to surveys of tourists. A noteworthy exception is a study by Bursa et al. (2022) that examined the revealed preference data of tourists in three alpine-touristic regions in Austria by

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modifying the concept of the travel diary to ask respondents about all their activities during a period of two days. Their survey design shows a lot of similarities but also differences to ours that we will explain below.

The data for this paper was obtained from a two-part-survey that we conducted in Kassel in two timeframes: one in September and October 2020; and the other one in August and September 2021. During both timeframes, the infection numbers of COVID-19 were very low in Germany resulting in relatively normal domestic tourism. The target of the survey were visitors to Kassel who did not visit the city for business purposes or an event. This included all overnight visitors as well as day visitors who arrived from places that were more than 25 km away from downtown Kassel. An overview of the survey structure and its different phases is summarized in figure 1.

The first part of the survey was held as a computer-assisted personal interview (CAPI) on weekends at several touristic hotspots in Kassel. The timeframes and places were chosen to maximize the number of visitors interviewed. The interviewers were trained to choose interviewees randomly. In practice, that meant that, due to the ongoing inflow of visitors, the interviewers approached the next arriving visitor after a successful interview or unsuccessful interview approach. We chose to recruit interviewees at the touristic hotspots because there was no feasible way of contacting them before they began their journey. This meant that the data produced is not representative of all visitors to Kassel, and a certain skewness is expected. Limiting the population to visitors to the touristic hotspots on the given days and times, we nonetheless regard the sampling as mostly random due to the approach chosen.

Visitors were distinguished from local people by several screening questions and then asked about sociodemographic information, their main reason for visiting Kassel, their mode of transport for the journey, the duration of their stay as well as planned, and visited touristic attractions in Kassel. Additionally, overnight visitors were asked about their accommodation during their stay. 2,050 visitors were interviewed in the first part of the survey. They consisted of 760 same-day and 1,290 overnight visitors.

Travel demand models usually rely on dividing the population into behaviorally homogeneous groups and applying the modeling steps for each one (Tang and Zhang, 2021, p. 71) (Schlick, 2003). Therefore, we decided to divide the visitors into behaviorally homogeneous groups based on their type of visit (overnight or daytime) and the mode of transport for their journey (by car or public transport). Two of these groups were chosen and interviewees from the first part belonging to one of the two groups were selected for the second part of the survey. We decided to choose the two largest groups of day visitors arriving by car and overnight visitors arriving by car to maximize the number of interviews in the second part of the survey.

The purpose of the second part of the survey was to survey all activities by a selected individual during the day he or she was interviewed for the first time. This was carried out in two ways. Most visitors were contacted again by telephone one or two days after they completed the first part of the survey and then interviewed again using a computer-assisted telephone interview (CATI). In this way, the interviewees were able to reproduce all the activities of their vacation day. As a certain non-response rate is expected, we decided to increase the response rate by preponing part two and conducting it right after part one of the survey for day visitors who responded that they would not participate in any more activities after the current one. Like Bursa et al. (2022), we used the concept of travel diaries as a basis to survey the activities of visitors, but we decided to separate the surveying of the activities from the general information time-wise. Bursa et al. chose a different approach whereby respondents could choose two past vacation days of their stay and report all activities in a personal interview at touristic relevant locations without a second interview after their stay. This approach was not feasible for us because of the short vacation durations of city tourists and the fact that we also interviewed day visitors.

The questionnaire regarding the activities comprised questions to gather the following information for each activity:

- Start and end time of the activity,
- Type of activity,
- Location,
- Mode of transport for arriving at the activity.

The arrival and departure to and from Kassel were treated as activities during the survey. In total, 1,186 intra-destination activities were collected from 397 visitors.

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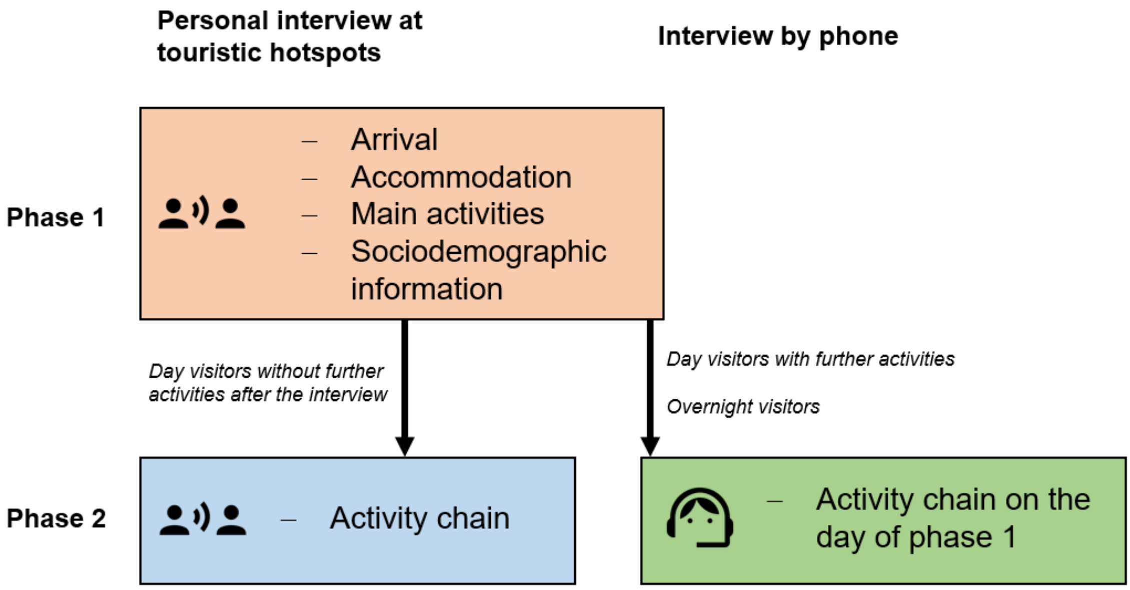

Figure 1. Overview of the different phases of the survey

2.3. Data preparation and enhancement

The activity data was transformed into trips for the model estimations. After that, all the location data (origin and destination) was geolocated as precisely as possible. To generate a revealed preference choice set, we routed all trips for the modes car, public transport and walking[1] with the aid of the HERE Routing API to determine the mode-specific travel times (here, 2022). Trips with imprecise location information for origin or destination were not considered in models that included the mode-specific variables because we could not determine feasible travel times. Additionally, sociodemographic as well as journey-related information was added to the dataset from the results of the first part of the survey.

Some hotels in Kassel offer their guests a free public transport ticket during their stay. We added the information regarding whether a visitor's hotel offers this ticket to its customers to our dataset to examine if this has an influence on their mode choice.

Additionally, we wanted to check if the service frequency of public transport at the place of stay has an influence on mode choice. We therefore added the number of public transport departures at the nearest stop to the location of the hotel as a proxy for the quality of public transport to the dataset.

Due to the popularity of the Bergpark, a great number of walking trips was made within the park or with the park as an origin and/or destination. We assume that a large share of these trips is part of the visit and therefore the trip itself is the activity. Mokhtarian and Salomon (2001) summarize this kind of trip and many others, including horse-back riding, cycling, etc., under the term 'undirected travel'. As the park is only accessible on foot, there is no mode choice process for the trips described. We therefore decided to exclude these trips from our dataset and model estimations.

2.4. Key values

The travel behavior varied heavily between day and overnight visitors. As arrival and departure are not part of on-site-mobility, 62.2 % of the day visitors did not make any additional trips in Kassel because they visited only one sight, mostly the Bergpark. Some visitors did only make undirected travel during their stay. We excluded these people and got a dataset of 129 trips from 82 day visitors and 476 trips from 151 overnight visitors. When only counting visitors who made on-site trips (excluding undirected travel), day visitors made on average 1.6 trips, whereas overnight visitors made 3.2 trips per person per day.

The modal split shows distinct differences between day and overnight visitors too (see figure 2). Day visitors had a much higher share of car usage, whereas far fewer trips were made by walking.

[1] Due to the very low number of trips by bike, cycling and using a taxi were not included as a mode choice.

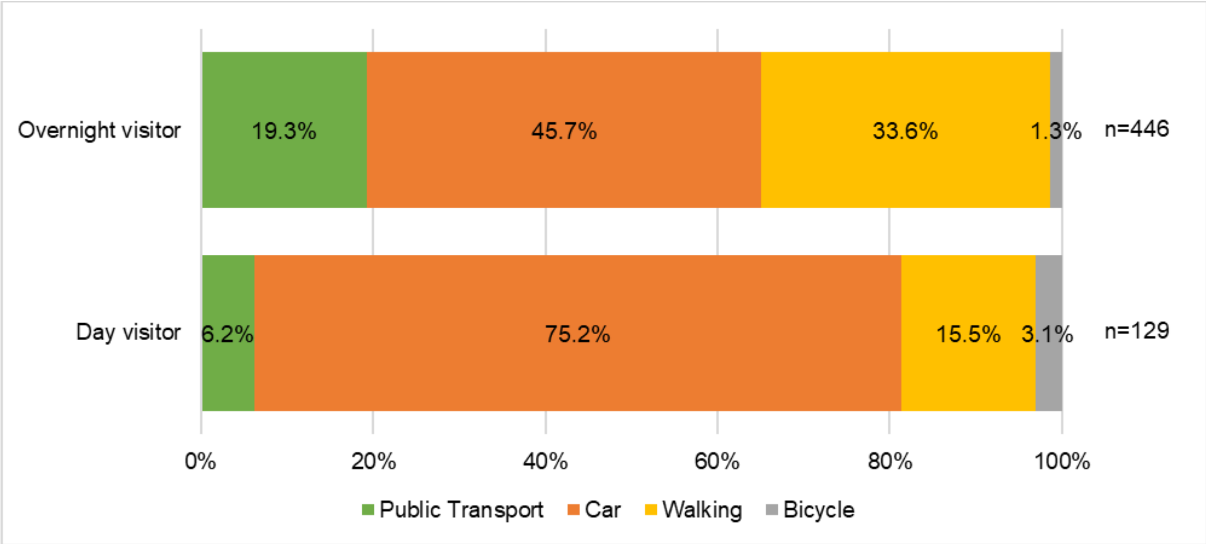

Figure 2. Modal split of the intra-destination trips of the visitors who arrived at Kassel by car.

2.5. Model estimation

To determine significant factors that influence mode choice, we used several multinomial logit models (MNL), also called logistic regression, that are widely used with data from discrete choice experiments. As described by Train (2012), the MNL determines the choice probabilities P_{ni} of a decision maker n for each alternative i from a choice set A_N as follows:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^{N} e^{V_{nj}}} \qquad (1)$$

The deterministic utility V_{nk} consists of one or more describing variables X_{ik} with corresponding coefficients β_{ik} and an alternative specific constant ASC_i, that considers the average utility effect of non-included variables:

$$V_{nk} = ASC_i + \beta_{i1}X_{ni1} + \cdots + \beta_{ik}X_{nik} \qquad (2)$$

Explanatory variables are either generic or alternative specific. Generic variables, like travel time and costs, vary over alternatives. In contrast, alternative specific variables attributed to the decision-maker, like sociodemographic information, do not vary between the alternatives in the choice set. Alternative specific variables as well as alternative ACS's enter the model, with one of the factors and/or constants normalized to zero for one alternative (Train, 2012). For our models, we have decided that this applies to the alternative public transport.

Because the MNL requires metric variables, categorical variables can only be implemented into a model if they are dummy-coded. We have, in most cases, chosen the group with the highest number of observations as the reference group. These groups are subsequently marked by '(ref.)'.

Table 2. Overview of the variables used in the model estimation

Category	**Variable**	**Generic**	**Alternative specific**	**Dummy coded**
Sociodemographic information	Age		X	
	Gender		X	X
	Number of cars in the household		X	
	Household size		X	
	Income		X	X
	Employment status		X	X
	Education level		X	X
Journey-related factors	Same-day or overnight visitor		X	X

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	Group Size		X	
	Children in travel group		X	X
	Single traveler		X	X
	Main reason for traveling		X	X
	Public transport service frequency at the hotel		X	
	Free public transport ticket at the hotel		X	X
Trip and mode related factors	Type of activity		X	X
	Travel time	X		

The model estimation was made using Biogeme, an open source Python package that allows users to estimate parameters, including the ASC's of discrete choice models with maximum likelihood estimation (Bierlaire, 2020). The variables that we included in the estimation have different response rates. Some only applied to overnight visitors and others had a higher non-response rate (e.g. household income) during the interviews. To estimate the significance of each variable with the maximum number of observations, we decided to estimate the factors of the variables described by creating several small models that included only one variable or variable group each. Any models that included alternative specific variables only were normalized to zero for the utility function of public transport V_{pt}. For models that included the generic variable travel time, respective parameters were estimated, but the ASC of public transport was set to zero.

Variables whose estimated factors showed at least a confidence level of 95 % were included in an overall model. Due to different response rates and correlations between the variables, far fewer factors of variables were significant when combined. So, we reduced the overall model to include only the significant factors. The utility functions of the final model V_{car} for using the car, $V_{walking}$ for walking and V_{pt} for using public transport are:

$$V_{car} = ASC_{car} + \beta_{activity\_return_{car}} \cdot ACTIVITY_{return} \tag{3}$$

$$V_{walking} = ASC_{walking} + \beta_{time_{walking}} \cdot TIME_{walking} \tag{4}$$

$$V_{pt} = ASC_{pt} = 0 \tag{5}$$

All utility functions consist of an ASC for the corresponding alternative. The utility function for car is dependent on the influencing variable $ACTIVITY_{return}$, which declares whether the activity for the trip is to return to the place of stay. For the alternative walking, the utility function consists of the variable travel time on foot $TIME_{walking}$. For both variables, the maximum likelihood estimation estimates the corresponding factors $\beta_{activity\_return_{car}}$ and $\beta_{time_{walking}}$.

3. Results

All the results are provided in detail in the appendix, in tables A1 to A4. The estimation results of the single models reveal that far fewer variables show significant influence on mode choice than presumed. Only gender, the reason for traveling, number of public transport departures at the hotel, type of activity and travel time were significant when estimating the models individually with reference to public transport:

- Gender: Negative influence on walking if gender is female,
- Reason for traveling: Negative influence on walking if visiting friends or family,
- Number of public transport departures at hotel: Positive influence on walking with growing number of departures,
- Activity of the trip: Negative influence on driving a car when the activity is a touristic activity, shopping or running errands, and returning to the place of stay,
- Travel time: Negative influence on walking with increasing travel time.

To interpret the data, we used adjusted McFadden $\bar{R}^2$-values. McFadden suggests that values between 0.2 and 0.4 "represent an excellent fit" (McFadden, 1977). All singular models produced results with adjusted $\bar{R}^2$-values below this threshold with the highest value for the model only including the travel times for each mode ($\bar{R}^2$ = 0.194). The quality of the estimated values is therefore not good enough to explain a sufficient part of the variance.

The final model consists of only the significant variables and factors from the individual models: Travel time for the alternative walking and the influence of activity return to place of stay (in comparison with all other types of activities) for the alternative car. It is notable that all non-trip-related variables resulted in non-significant factors. The longer the travel time, the lower the utility of the alternative walking and therefore also its probability. This effect is compensated for shorter trips through a higher alternative specific constant in comparison with the other alternatives. Ignoring other influencing factors, walking has the highest utility of all alternatives for up to 34.6 minutes. As no time factors for the other alternative were significant, their utility does not depend on travel time. For the alternative car, there is a negative influence on the utility if the reason for the trip is to return to the place of stay (for example the hotel). Comparing this effect to the influence of travel time on walking, this means that the utility loss if the trip's purpose is to return to the place of stay is equal to the utility of 33.8 minutes' walking. The model quality can be interpreted differently. The adjusted McFadden $\bar{R}^2$ of 0.215 is at the lower end but within the described range for excellent fit, meaning that the model can reproduce mode choice. On the other hand, comparing it to other models, especially mode choice models for alpine tourists by Bursa (2021) our estimations have a distinctly lower goodness of fit with distinctly less significant influencing variables.

Compared to other research, it is notable that in our final model only the trip-specific variables were significant whereas sociodemographic and trip-related variables remained non-significant.

Table 2. Estimation results of the final mode choice model.

	Final Model	
	Car	Walking
Activity: Return to place of stay	-1.21*	/
Activity: All other activities (ref.)	/	/
Travel time (min)	/	-0.0358**
ASC	0.992**	2.23**
Likelihood ratio test	76.89256	
Adjusted McFadden R^2	0.215	
Observations	146	

* $p < 0.05$, ** $p < 0.01$.

4. Discussion and conclusion

In contrast to mode choice models that describe everyday travel behavior, our estimations did not produce results that describe the mode choice behavior of touristic intra-destination travelers sufficiently enough. We were especially surprised that travel time shows only a significant influence on walking whereas no dependence on travel time was proven for using public transport or driving by car. This contradicts research for everyday travel behavior and the findings for alpine tourism by Bursa (2021). The question arises as to whether travel time is less important for city tourists' mode choice or if mode choice models that only consider single trips are not sufficient for modeling intra-destination mode choice behavior. City tourists might be less time sensitive and undirected travel plays a bigger role for them than in everyday mobility. This would have a direct influence on the possibility of evaluating traffic measures that affect tourists because changes in travel time would have no or minor effects on the modal split.

We assume that modeling trip chains instead of single trips could improve the quality of models. In everyday mobility, trip chains start and end at the home location. In the case of tourists, this would mean that trip chains start and end at the place of accommodation or upon arrival or departure. Trip chains can be unimodal if all trips in the chain are made using the same mode of transport or they can be multimodal if more than one mode of transport is used. (Schneider et al., 2021)

Mode choice modeling of trip chains usually relies on the complexity and/or the main activity of a chain. Complexity means the number of trips that the chain comprises. In everyday mobility, research suggests that unimodal trip chains by public transport are predominately simple whereas chains that are more complex are more often carried out by car. Multimodal trip chains, however, are often complex or very complex. (Schneider et al., 2021)

The main activity of a trip chain that defines the mode choice is identified in different ways. A common approach is a hierarchical ranking of activity types as carried out by Frank et al. (2007) with activities related to work, university or school having a higher prioritization than eating out or incidental shopping.

Because touristic activities differ from everyday mobility, trip chain approaches must be adjusted to describe touristic behavior. We imagine that a combined approach based on complexity and defining a chain's primary activity could be promising. Touristic activities might generally be the primary activity of a chain if present. Additionally, if multiples of the same types of activity exist in a chain, for example different touristic activities, the primary activity also needs to be identified amongst activities of the same kind. A possible approach would be to choose the activity with the location that is the most far away from the accommodation or place of arrival/departure.

No matter which approach is chosen, modeling trip chains that include travel times requires better quality data than using single trips. This is because a mode choice set for all trips of a chain needs to be reconstructed meaning that the location information of all activities must be precise. Unfortunately, the data quality of our survey was not good enough to estimate travel times for all modes of transport for all trips in the chains. To improve data quality, a mixed approach that combines location data generated by mobile phones with a phone-based survey that lets users correct data, like mode of transport and type of activity, as well as answer questions about sociodemographic and mobility related information might be promising. Mobile applications, like "TravelVu", that was tested by Hubrich et al. (2020) in the city of Dresden, Germany already offer these capabilities. Of course, in comparison with our survey, recruiting participants is more complicated and costly, resulting in a lower sample size.

We conclude, based on our empirical results, that modeling the travel behavior of tourists is more complex than modeling everyday mobility. This is partly to do with a lack of data. While it is common for cities to regularly conduct travel surveys on everyday mobility, to our knowledge no city collects the revealed preference data of tourists' mobility. Furthermore, tourists' travel behavior differs from everyday mobility and it is, therefore, not clear how large the influence of travel time is on mode choice. Tourists might be less time sensitive and, because they have a lot of undirected travel, time might have no influence at all for some trips. Overall, there is a distinct need for further research, especially to generate more and better data on city tourists' travel behavior.

Appendix

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Table A1. Estimation results model 1 to model 4

	Model 1		Model 2		Model 3		Model 4	
	Car	Walking	Car	Walking	Car	Walking	Car	Walking
Gender: female	-0.289	-0.734*						
Gender: male (ref.)	/	/						
Age	0.0127	0.0101						
Cars in household			-0.00169	0.389				
Household size			0.0941	-0.151				
Income: < 1500€					0.588	-0.105		
Income: 1500€ - 2000€					23.9	23.4		
Income: 2000€ - 3000€ (ref.)					/	/		
Income: 3000€ - 4000€					0.777	0.951		
Income: 4000€ - 5000€					0.693	-1.9		
Income: 5000€ - 6000€					-0.393	-0.799		
Income: > 6000€					22.6	23.2		
Employment: Employee							0.272	0.271
Employment: Student							0.0645	0.365
Employment: Pensioner (ref.)							/	/
ASC	0.7	0.341	0.901*	0.0756	0.511	0.105	0.965*	0.223
Likelihood ratio test	69.56497		69.92239		68.38285		66.9549	
Adjusted R^2	0.0891		0.0897		0.081		0.0875	
Observations	294		294		227		286	

* $p < 0.05$, ** $p < 0.01$.

Table A2. Estimation results model 5 to model 8

	Model 5		Model 6		Model 7		Model 8	
	Car	Walking	Car	Walking	Car	Walking	Car	Walking
Education level: Hauptschulabschluss	0.177	0.354						
Education level: Realschulabschluss	0.965	0.824						
Education level: Fachhochschulreife	0.366	0.354						
Education level: Abitur (ref.)	/	/						
Same-day visitor			0.692	-0.812				
Overnight visitor (ref.)			/	/				
Number of nights					0.0156	0.15		
Group size							-0.0197	0.123
ASC	0.922**	0.206	0.935*	0.1	1.17**	0.0949	1.17**	0.0949
Likelihood ratio test	69.74636		38.43889		66.50265		66.50265	
Adjusted R^2	0.0838		0.0565		0.0903		0.0903	
Observations	292		245		295		295	

* $p < 0.05$, ** $p < 0.01$.

Table A3. Estimation results model 9 to model 11

	Model 9		Model 10		Model 11	
	Car	Walking	Car	Walking	Car	Walking
Accompanying Children: Yes	0.446	-1.17				
Accompanying Children: No (ref.)	/	/				
Single traveler: Yes	0.533	0.214				
Single traveler: No (ref.)	/	/				

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Reason: City/cultural trip (ref.)			/	/		
Reason: Health vacation			22.6	22.6		
Reason: Active holiday			21.9	20.5		
Reason: Visiting friends/family			-0.151	-0.964*		
Reason: Visiting an event			-0.24	-59.8		
Reason: Private errands			28.1	27.3		
Public transport frequency at the hotel					0.00414	0.0167*
Free PT ticket at hotel: Yes					-0.826	-0.446
Free PT ticket at hotel: No (ref.)					/	/
ASC	0.971**	0.48	1.09**	0.676**	0.845*	-0.0616
Likelihood ratio test	77.33985		89.41038		25.73572	
Adjusted R^2	0.101		0.101		0.0406	
Observations	295		295		154	

* $p < 0.05$, ** $p < 0.01$.

Table A4. Estimation results model 12 to model 13

	Model 12		Model 13		
	Car	Walking	Car	PT	Walking
Activity: Bergpark (ref.)	/	/			
Activity: Touristic Activity	-1.16*	0.362			
Activity: Restaurant	-0.56	1.09			
Activity: Shopping/errands	-1.81**	-0.118			
Activity: Visiting	-2.06	-0.811			
Activity: Return to place of stay	-1.7**	0.154			
Travel time (min)			0.014	-0.035	-0.036**
ASC	2.06**	0.118	-0.496	0	1.16*
Likelihood ratio test	94.87898		69.97923		
Adjusted R^2	0.112		0.194		
Observations	287		142		

* $p < 0.05$, ** $p < 0.01$.

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