MODELLING ROUTE CHOICE DECISIONS OF CAR TRAVELLERS USING COMBINED GPS AND DIARY DATA

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ABSTRACT

The aim of this research is to identify the relationship between activity patterns and route choice decisions. The focus is twofold: on the one hand, the relationship between the purpose of a trip and the road categories used for the relocation is investigated; on the other hand, the relationship between the purpose of a trip and the deviation from the shortest path is studied. The data for this study were collected in 2006 and 2007 in Flanders, the Dutch speaking and northern part of Belgium. To estimate the relationship between the primary road category travelled on and the corresponding activity-travel behaviour a multinomial logit model is developed. To estimate the relationship between the deviation from the shortest path and the corresponding activity-travel behaviour a Tobit model is developed. The results of the first model point out that route choice is a function of multiple factors, not just travel time or distance. Crucial for modelling route choices or in general for traffic assignment procedures is the conclusion that activity patterns have a clear influence on the road category primarily driven on. Particularly, it was shown that the likelihood of taking primarily through roads is highest for work trips and lowest for leisure trips. The second model shows a significant relationship between the deviation from the shortest path and the purpose of the trip. Furthermore, next to trip-related attributes (trip distance), also socio-demographic variables and geographical differences play an important role. These results certainly suggest that traffic assignment procedures should be developed that explicitly take into account an activity-based segmentation. In addition, it was shown that route choices were similar during peak and off-peak periods. This is an indication that car drivers are not necessarily utility maximizers, or that classical utility functions in the context of route choices are omitting important explanatory variables.

KEYWORDS: route choice modelling, shortest path, road category, trip purpose, activity-based approach

1 INTRODUCTION

To support policy makers, traffic and transportation models can be used to make better long-term decisions. On an international level, activity-based models have become the norm to model travel behaviour (Davidson et al., 2007). The most important characteristic of these models is that the travel behaviour of persons or families is a product of the activities that they wish or have to perform, procuring a more realistic description and a better understanding of people's travel behaviour (Cirillo et al., 2012; Flötteröd et al., 2012). Because of these advantages, researchers and policy makers in the United States have switched from conventional models to activity-based models. Although this trend is most visible in the United States, a similar evolution can be noticed in Europe. Governments require reliable predictions of travel behaviour, traffic performance, and traffic safety to support long-term decisions. A better understanding of the events that influence travel behaviour and traffic performance will lead to better forecasts and consequently policy measures that are based on more accurate data.

In transportation models, modelling route choice behaviour is essential to forecast travellers' behaviour under hypothetical scenarios, to predict future traffic conditions on transportation networks and to understand travellers' reaction and adaptation to sources of information (Prato, 2009). An important limitation in both traditional four-step and present-day activity-based models is the fact that current route choice models have been developed largely in the absence of objective empirical evidence of actual route choices. Theories of utility maximization have proven useful (Ramadurai and Ukkusuri, 2010), but the underlying behaviour realism of these theories, when applied to modelling route choices, has not been extensively validated by empirical studies (Jan et al., 2000). After all, confronted with a multitude of route choice facets, travellers may not be able to make optimal decisions, especially when the deliberation process of various possible routes involves the anticipation of congestion (Han et al., 2008). Moreover, route choice decisions are based on existing knowledge and experiences that irrefutably influence the evaluation of the different choice alternatives (Papinski et al., 2009). E.g., travelers may not consider all the possible routes but have several pre-trip routes in mind prior to their departure, which are selected from their day-to-day traveling experiences (Qian and Zhang, 2012).

The aim of this research is to identify statistically significant relationships between activity patterns and the behaviour regarding route choice. The focus of this paper is twofold. On the one hand, the relation between the purpose of a trip and the road categories used for the relocation is studied as only a limited number of studies can be found in literature, in which the relationship between the purpose of the trip and the road categories used for the relocations is analyzed. On the other hand, the focus is on the relationship between the purpose of the trip and the deviation from the shortest route. Since literature shows that other factors besides route attributes (personal, household and situational characteristics) play a role in route selection, personal characteristics as age, gender, income, profession and province and the situational characteristic time of day are considered in the analyses. If this research confirms the importance of the purpose of the trip in route selection, traffic assignment procedures should be developed that explicitly take into account trip purpose. For example, different utility functions for trips with different trip purposes may be used.

The paper is organised as follows: in the next section, a literature review is provided. In the third section, the data is described. In section 4, the adopted methodology approach is explained in further detail and the results are discussed. Finally, in section 5, the most important findings are summarised and directions for further research are highlighted.

2 LITERATURE REVIEW

A number of studies have been performed in the past on route choice, as summarized in Table 1. Early studies mainly focused on the travel time. Minimizing travel time is considered the most important criterion affecting drivers' route choice as found by Duffell and Kalombaris (1988), Huchingson et al. (1977), and Wachs (1967). Also, directness (Huchingson et al. 1977) and less congestion (Wachs, 1967) were among the important reasons. The reliability of a particular route can also be expected to play an important role in the traveller's route choice behaviour. In several attitudinal studies, reliability-related attributes have been found among the most important service attributes in a variety of situations (Jackson and Jucker, 1981). Jou and Mahmassani (1994) and Mannering et al. (1994) found that socioeconomic characteristics together with the traffic network were also important determinants of route changing behaviour.

Abdel-Aty and Huang (2004) state that route choices are a function of multiple factors, not limited to cost variables such as travel time and distance. Literature shows that other factors besides route attributes (personal, household and situational characteristics) play a role in the route selection. Zhang and Levinson (2008) state that enhanced roadside aesthetics have the most significant effect on recreational trips. According to Parkany et al. (2006), a wide variety of data variables – travel habits, personal attitudes, route characteristics, demographic and revealed data – are related to route choice. Peeta and Yu (2005) state that driver en-route routing decisions are influenced by personal attributes, response attitude to the supplied information, and situational factors such as time-of-day, weather conditions, trip purpose, and ambient traffic conditions.

Several studies regarding route choice focus on commuting route choice behaviour. Abdel-Aty et al. (1997) present a statistical analysis of commuters' route choice including the effect of traffic information. Empirical research on route choice behaviour shows that drivers use numerous criteria in formulating a route: travel time, number of intersections, traffic safety, traffic lights and other factors. Assuming travel time as the sole criterion of route choice is thus an unrealistic abstraction of individual behaviour and may result in an inaccurate representation of traffic. Among the socioeconomic factors gender has a significant effect on route choice. Papinski et al. (2009) study route choices for the home-to-work commute. The study explores potential reasons for route selection. The survey investigates both network-based (travel time, distance) and non-network-based (comfort, safety, routine) attributes. Kaplan and Prato (2012) show the importance of incorporating spatiotemporal constraints and latent traits such as habitual behaviour, time saving skills and network familiarity in route choice models.

Few studies examine observed route choice behaviour. However, the exploration of observed route choice behaviour is crucial because the underlying decision-making process is more complex and dynamic for route choice than for other travel choice dimensions. The difficulties associated with the collection of data on route choice are reflected in the scarcity of studies on observed behaviour and the major simplifications made in traffic assignment models developed for the most common commercial software (Spissu et al., 2011).

With the emergence of activity-based models, the relationship between trip purpose and route choice became an interesting topic to study. Studies regarding the relationship between the purpose of the trip and the travel distance are frequently available. Zhang and Levinson (2008) state that the shortest path is chosen less when the purpose of the trip is shopping or paying a visit rather than travelling to work or to a leisure activity. Goldenbeld et al. (2007) study the route choice of car travellers in the Netherlands. Almost half of the respondents indicates 'shortest path' as one of the main reasons for choosing a route. When the purpose of the trip is work, ‘shortest path’ is considered more important in route choice than for other trip purposes. Levinson and El-Geneidy (2009) used network circuity, which is defined as the ratio between road network distance and Euclidean distance, to understand home-work trips. The authors found that workers are more likely to commute with lower circuity to save travel time. Huang and Levinson (2012) conclude from their research on non-work non-home trips, that travel time has the most significant impact on destination choice. Destinations that are farther away are also less favorable. Moreover, discontinuous routes and more circuitous routes are less attractive. In a study of Papinski et al. (2009), route directness is indicated as the second most important factor when choosing a route. Jan et al. (2000) state that in most instances the chosen path differs considerably from the shortest path across the network. According to Zhang and Levinson (2008) efficiency-related attributes such as travel time, distance and number of stops are considered more important for commute, event and visit trips and less important or even insignificant for shopping and recreational trips.

Currently, studies regarding the shortest path hypothesis irrespective of the trip purpose are widely available. Results from a study by Bekhor et al. (2006) indicate that 37% of respondents follow the shortest time path compared to 22% following the shortest distance path. Prato and Bekhor (2006), on the other hand, found that 53.5% of respondents chose the shortest distance path while 43.3% chose the shortest time path. Neither of both studies investigates the influence of trip purposes. Zhu (2010) investigated route choice behavior and evaluated the gap between the shortest-path assumption and the route decisions observed, using GPS and survey data collected in the Twin Cities, Minnesota, after the collapse of the I-35W Mississippi River Bridge. The data indicates that 18 of 59 respondents chose the shortest path consistent with that computed on a planning network before the bridge collapsed, while 8 of 37 respondents chose the shortest path after the bridge collapsed.

Only a limited number of studies can be found in literature, in which the relationship between the purpose of the trip and the road categories used for the relocations is analyzed. Zhang and Levinson (2008) investigated the factors influencing route choice to assess the value of traveller information. They tried to unravel the route selection process with and without traveller information for different trip purposes. From their results, it is evident that the importance of route attributes varies with trip purposes. Murakami and Wagner (1999) ascertained that only a very small amount of variation in the use of road categories is due to different trip purposes. Ramming (2002) stated that car travellers want to minimize their travel time, regardless of the purpose of the trip, and therefore they choose primary roads. This finding is confirmed by Li (2004) and by Zhu (2010), who point out the importance of the functional classification of roads, mainly emphasizing a higher use of freeways (in comparison with the use of local streets). Furthermore, Levinson and Zhu (2012) analyzed GPS data to determine which type of roads users chose when travelling, regardless of the trip purpose. From this, it appears that more than half of the travel on county roads and city streets occur outside of one’s home city. Most travel, however, is within one’s home county. According to Parthasarathi (2011) and Parthasarathi et al. (2012), hierarchy, topology, morphology, and the scale of road networks affect household spatial activities, road congestion levels, but most importantly trip distances and the daily vehicle kilometers traveled per capita.

TABLE 1 Literature Review

Route choice behavior in general	
Duffel and Kalombaris, 1988; Huchingson et al., 1977; Wachs, 1967	'(Minimizing) Travel time' is the most important criterion
Huchingson et al., 1977	'Directness' is also expected to play an important role
Wachs, 1967	'(Less) Congestion' is also expected to play an important role
Jackson and Jucker, 1981	Reliability-related attributes are among the most important attributes
Jou and Mahmassani, 1994; Mannering et al., 1994	Socio-economic characteristics and the traffic network are important determinants of route changing behavior
Abdel-Aty and Huang, 2004	Route attributes (travel time and distance) and other factors (personal, household and situational characteristics) play a role in route choice behavior
Zhang and Levinson, 2008	Significant effect of enhanced roadside aesthetics on recreational trips
Parkany et al., 2006	Travel habits, personal attitudes, route characteristics, demographic and revealed data are related to route choice
Peeta and Yu, 2005	Driver en-route routing decisions are influenced by personal attributes, response attitudes to the supplied information and situational factors (time-of-day, weather conditions, trip purpose, ambient traffic conditions)
Abdel-Aty et al., 1997	Travel time, number of intersections, traffic safety, traffic lights and other factors play a role in commuters' route choice behavior. Gender has significant effect on commuters' route choice
Papinski et al., 2009	Impact of network-based (travel time, distance) and non-network based (comfort, safety, routine) attributes on the home-to-work commute.
Relationship between trip purpose and travel distance (≈ deviation from shortest path)	
Zhang and Levinson, 2008	Shortest path is chosen less for shopping and visit trips than for work or leisure trips. Efficiency-related attributes (time, distance, number of stops) are important for commute, event and visit trips and insignificant for shopping and recreational trips
Goldenbeld et al., 2007	'Shortest path' is one of the main reasons for choosing a route (in a study in the Netherlands) and is more important for route choice of work trips than for other purposes
Levinson and El-Geneidy, 2009	Workers are more likely to commute with lower circuity
Huang and Levinson, 2012	Non-work non-home destinations that are farther away, and discontinuous or more circuitous routes are less attractive
Papinski et al., 2009	Route directness as second most important factor for route choice
Jan et al., 2000	Mostly, the chosen path differs considerably from shortest path
Bekhor et al., 2006	37% of respondents follow shortest time path, 22% follow shortest distance path
Prato and Bekhor, 2006	43.3% of respondents follow shortest time path, 53.5% follow shortest distance path
Relationship between trip purpose and road category	
Zhang and Levinson, 2008	The importance of route attributes varies with trip purpose
Murakami and Wagner, 1999	Only very small variations in the use of road categories is due to different trip purposes
Ramming, 2002	Car travelers minimize travel time and choose primary roads, regardless of trip purpose
Li, 2004; Zhu, 2010	Higher use of freeways, regardless of trip purpose
Levinson and Zhu, 2012	More than half of the travel on county roads and city streets occur outside of one's home city. Most travel is within one's home county
Parthasarathi, 2011; Parthasarathi et al., 2012	Hierarchy, topology, morphology, and scale of road networks affect household spatial activities, road congestion levels, trip distances and daily vehicle kilometers traveled per capita

3 DATA

The data for this study were collected in 2006 and 2007 in Flanders, the Dutch speaking and northern part of Belgium (see Figure 1). The data was collected for a 7-day period. The survey used a mixed-mode survey design, using a PDA application on the one hand, and using traditional paper and pencil diaries on the other hand. The PDA application, called PARROTS (PDA (Personal Digital Assistant) system for Activity Registration and Recording of Travel Scheduling) has been developed in such that respondents could easily provide information about their activity-travel behaviour (Bellemans et al., 2008). Whenever an activity or trip is registered in PARROTS, a number of attributes for this activity or trip were collected using a customized graphical user interface. The most important activity and trip attributes PARROTS collected are: activity type, date, start and end time, location, mode of transportation, travel time and travel party. Besides, PARROTS uses the integrated Global Positioning System (GPS) to automatically record location data. This combination of GPS and diary responses provides great insight into the route choice decision-making process (Papinski et al., 2009). Jan et al. (2000) showed that GPS is a viable tool to study travellers' route choice decisions as GPS can reveal important travel behavioural information that is impossible to discern with earlier conventional survey methods such as interviews, respondent-administered questionnaires, or driver simulators. Moreover, conventional methods have proved burdensome, time consuming, and error prone (Wolf et al., 1999).

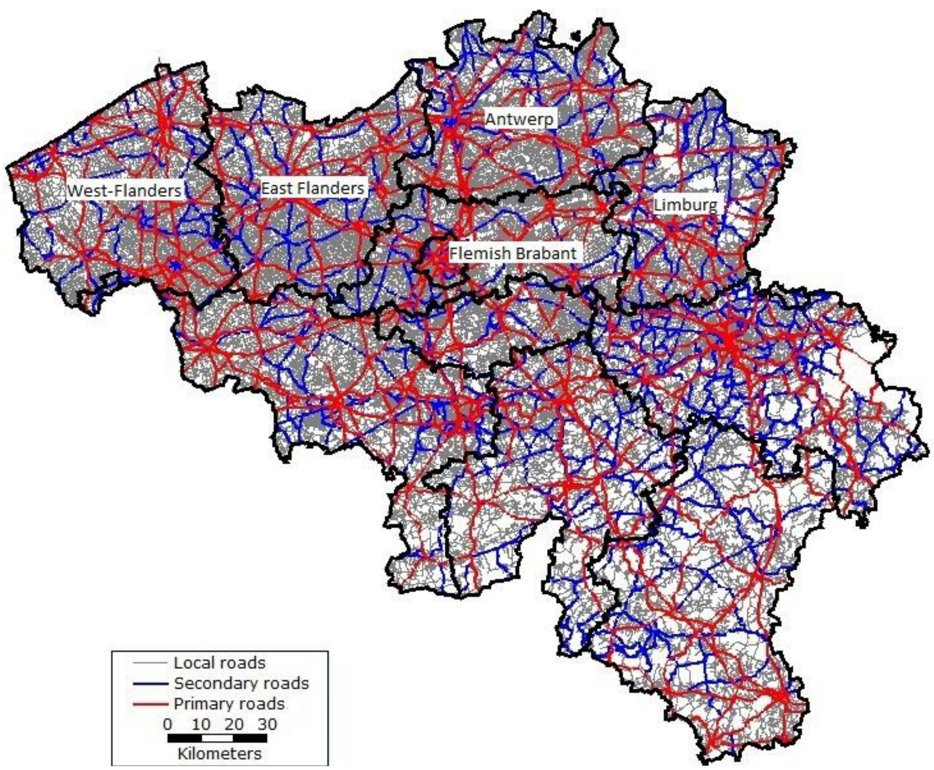

FIGURE 1 Map of Belgium

In order to analyze the reported and recorded travel data, advanced post-processing is necessary to make the information usable for route choice modelling (Schuessler et al., 2010). In this research only displacements made by car are taken into account. Displacements made with any other mode of transport are filtered out of the database. Next, the GPS-data are compared to the data reported by the respondents in the diaries. If there is a mismatch between both data sources, the displacements are not used in the analyses since it is possible that the reported displacements are incorrect. Furthermore, only respondents that filled in all personal characteristics are considered because these characteristics are used in the analyses. Given the network that is used to analyze the trips is a national network (see Figure 1 for the network structure and Table 2 for a quantitative description), cross-border displacements are removed from the database. The data processing step, which integrated automatic trip detection algorithms as well as manual correction and map matching, leads to a dataset containing car displacements on the Belgian road network for respondents of whom the personal characteristics are known and for whom the GPS-data is consistent with the data reported in the diaries. The dataset contains 1423 car displacements, made by 299 different respondents.

TABLE 2 Description of the Road Network

Province	Number of links			Length of the network (km)		
	Through road	Distributor road	Access road	Through road	Distributor road	Access road
Antwerp	4938	4106	77722	1062,7	655,6	12346,8
Limburg	3424	3988	52723	747,5	626,8	8848,0
East Flanders	5418	3593	71707	1220,5	556,2	11696,2
West Flanders	6277	3472	66718	1231,7	558,9	11113,6
Flemish Brabant	6261	2845	79419	1096,0	391,4	10970,9

The focus in this study is turned to the relationship between the purpose of a trip and the road categories used for the relocation or the deviation from the shortest route. In this paragraph, the variables that are used in the analyses are described. Roads are divided in three categories, following the functional road classification of Weijermars et al (2008), namely through-roads (primary roads), distributor roads (secondary roads) and access roads (local roads). The primary road category travelled on is defined as the road category for which the proportion of this class distance to total chosen route distance is highest. Furthermore, trip-related attributes are considered. In literature these attributes are often pinpointed as predominant variables including: trip purpose (de Palma and Picard, 2005), trip distances (Scheiner, 2010) and congestion (Jan et al., 2000). Five types of trip purposes are distinguished: work, leisure, shopping, home and other. Congestion is coded as a dummy taking value one for trips made during congested periods (6:00-9:00 and 16:00-19:00) and taking value zero during other periods of the day. Besides trip-related attributes, other factors such as socio-demographic and geographical characteristics play an important role in the route selection, as discussed by de Palma and Picard (2005), Bayarma et al. (2007) and Li et al. (2005). Therefore, the personal characteristics age, gender, net personal income, profession and the geographical characteristic province are considered in the analyses.

Table 3 provides a descriptive overview of the route choices, i.e. the road categories chosen, for the various levels of the explanatory variables. Note that the continuous variables distance and age have been categorized for the tabulation of this table. First, the table displays the total number of trips that are carried out by each level of the categorical variables. For example, from the 1423 car displacements that are used in this study, 945 trips are carried out by men and 478 trips are carried out by women. Next, the table displays for each level of the categorical variables the percentage of trips that are mainly carried out on the different road categories. In addition, the results (p-values) of the chi-square independence test, testing the hypotheses that the route choice is independent of the predictor investigated, is given. In accordance with international literature, the descriptive results in this table point out that trip-related attributes, as well as socio-demographic and geographical characteristics, appear to have an impact on the route choice. Concerning trip purpose, for work-related trips about 15% more trips are made on through roads when compared to trips with other trip purposes. One explanation is the fact that, on average, trip distances for work-related trips are longer than other trips, and in general longer trips are mainly carried out on through roads. This is supported by the figures in Table 3 revealing a 4 times bigger share of through road trips exceeding 20 km compared to small trips of less than 5 km. Congestion appears to have no effect on the road category travelled by. This is in line with Parkany et al (2006) who state that the majority of people follow the same route during peak and off-peak conditions. Notwithstanding, the research presented in this paper only shows similarities concerning the road category, but does not indicate per se that routes are similar.

TABLE 3 Road Categories Chosen for the Different Levels of the Predictors

	Total	Through road		Distributor road		Access road		
Category	**# Trips**	**# Trips**	**% Trips**	**# Trips**	**% Trips**	**# Trips**	**% Trips**	**P-value**
Overall	1423	566	39.78%	182	12.79%	675	47.43%	
Trip purpose								<0.001
- Home	423	164	38.77%	42	9.93%	217	51.30%	
- Work	281	146	51.96%	47	16.73%	88	31.32%	
- Shopping	208	77	37.02%	24	11.54%	107	51.44%	
- Leisure	259	95	36.68%	37	14.29%	127	49.03%	
- Other	252	84	33.33%	32	12.70%	136	53.97%	
Distance								<0.001
- 0-5 km	544	106	19.49%	51	9.38%	387	71.14%	
- 5.1-10 km	307	91	29.64%	48	15.64%	168	54.72%	
- 10.1-20 km	297	151	50.84%	45	15.15%	101	34.01%	
- >20 km	275	218	79.27%	38	13.82%	19	6.91%	
Congestion								0.482
- Off-peak	791	307	38.81%	108	13.65%	376	47.53%	
- During peak	632	259	40.98%	74	11.71%	299	47.31%	
Age								0.120
- 18-25	96	49	51.04%	5	5.21%	42	43.75%	
- 26-40	405	166	40.99%	55	13.58%	184	45.43%	
- 41-64	858	328	38.23%	115	13.40%	415	48.37%	
- 65+	64	23	35.94%	7	10.94%	34	53.13%	
Gender								<0.001
- Male	945	347	36.72%	151	15.98%	447	47.30%	
- Female	478	219	45.82%	31	6.49%	228	47.70%	
Profession								0.012
- Blue-collar worker	104	35	33.65%	21	20.19%	48	46.15%	
- White-collar worker	815	335	41.10%	105	12.88%	375	46.01%	
- Independent	69	36	52.17%	7	10.14%	26	37.68%	
- Student	43	22	51.16%	2	4.65%	19	44.19%	
- Not professionally active	301	100	33.22%	34	11.30%	167	55.48%	
- Other	91	38	41.76%	13	14.29%	40	43.96%	
Net personal income								<0.001
- 0-1250 €	177	49	27.68%	16	9.04%	112	63.28%	
- 1250-1750 €	401	175	43.64%	48	11.97%	178	44.39%	
- 1750-2250 €	393	149	37.91%	63	16.03%	181	46.06%	
- 2250-2750 €	132	63	47.73%	8	6.06%	61	46.21%	
- >2750 €	65	29	44.62%	12	18.46%	24	36.92%	
- No answer	255	101	39.61%	35	13.73%	119	46.67%	
Geographic region								<0.001
- Antwerp	380	145	38.16%	50	13.16%	185	48.68%	
- Limburg	325	127	39.08%	80	24.62%	118	36.31%	
- East Flanders	258	126	48.84%	13	5.04%	119	46.12%	
- West Flanders	107	53	49.53%	10	9.35%	44	41.12%	
- Flemish Brabant	353	115	32.58%	29	8.22%	209	59.21%	

P-value corresponds to the p-value of the chi-square independence test.

When the focus is turned to the socio-demographic characteristics it becomes apparent that younger people travel relatively more by through roads, whereas older have a higher share in routes that predominately travel across access roads. Concerning gender differences, one can notice that the higher share of females in through roads is compensated by a higher share on distributor roads for males. The percentage of routes that is mainly travelled by access roads is almost the same. With respect to profession the small share of distributor roads for students and the large share of access roads for professionally inactive persons attract attention. With regard to net personal income one can notice a clear difference between the lowest income category and the other income categories: the share of trips mainly carried out on access roads is distinctly higher than other income groups. Finally, also geographical differences seem to play a non-ignorable role. In East and West Flanders, through roads are mostly used, while in Antwerp and Flemish Brabant, access roads are mostly used. A possible explanation is the fact that Antwerp and Flemish Brabant are the Belgian provinces with the most congestion, so people trying to find alternative routes via access roads. Because there are less through roads in Limburg (see e.g. Table 2), distributor roads are used more in this province.

4 METHODOLOGY AND RESULTS

4.1 Choice Primary Road Category (Selected Road Hierarchy)

In the first part of this study, the focus is to assess the relationship between the primary road category travelled on and the corresponding activity-travel behaviour. The primary road category travelled on is the road category for which the proportion of this class distance to total chosen route distance is highest. To estimate this relationship a multinomial logit model (MNL) is developed. In this regard, it is important to point to the difference between a multinomial logit model (MNL) on the one hand, and a condition logit model (CL) on the other. As indicated by Hoffman and Duncan (1988), the MNL focuses on the individual (in this study the individual trip) as the unit of analysis and uses the individual's characteristics as explanatory variables (in the previous section, an elaborate description of the considered trip-related attributes was provided). In contrast, the CL focuses on the set of alternatives for each individual (i.e. the trip) and the explanatory variables are characteristics of those alternatives. Let *Y* (the primary road category travelled on) be the response variable, $y_i = (y_{i1}, y_{i2}, y_{i3})^T$, that has a multinomial distribution $\pi_i = (\pi_{i1}, \pi_{i2}, \pi_{i3})^T$, and let *X* be a set of explanatory variables (discrete and/or continuous). Taking *j** as the baseline category (i.e. access roads in this study), the model can be represented by the following equation:

$$\log\left(\frac{\pi_{ij}}{\pi_{ij^*}}\right) = x_i^T \beta_j, \qquad j \neq j^* .$$

To assess the significance of the various trip-related and non-trip related predictors, a type III analysis of the effects is made, displayed in Table 4. In contrast to the individual parameters, which are provided in Table 5, the overall type III analysis pinpoints which variables significantly explain differences in the main road hierarchy driven on. Even if the individual parameter estimates are not significant, still the overall variable can explain significantly the relationship with the road hierarchy. After all, the significance of the individual parameter estimates depends on the (arbitrary) choices of the reference category for the choice alternative (i.e. access roads) and the reference category of the categorical explanatory variables. Note that, in line with Parkany et al (2006), congestion has no significant impact on the modelled route choice decisions. Therefore congestion will not be included in the final model. Moreover, according to the Akaike information criterion (AIC), the model without congestion should be preferred. In accordance with international literature (see e.g.

Abdel-Aty and Huang (2004) and Parkany et al (2006)), and in line with the descriptive statistics presented in Table 3, next to trip-related attributes (trip purpose and trip distance), also socio-demographic variables and geographical differences play a noticeable role. Important to underline is the importance of the activity-based segmentation: there is a clear relationship between the route choice (road type) and the activities people perform.

TABLE 4 Primary Road Category (MNL) Model: Type III Analysis of Effects

Effect	DF	Wald Chi-Square[1]	P-value[1]	Wald Chi-Square[2]	P-value[2]
Purpose	8	17.590	0.025	16.601	0.035
Distance	2	217.904	<0.001	218.331	<0.001
Congestion	2	1.785	0.410		
Age	2	6.881	0.032	7.033	0.030
Gender	2	26.426	<0.001	26.370	<0.001
Profession	10	20.575	0.024	20.990	0.021
Net personal income	10	24.897	0.006	24.859	0.006
Geographic region	8	81.757	<0.001	82.482	<0.001
Log likelihood		-1070.713		-1071.612	
AIC		2233.426		2231.223	
McFadden R^2		0.235		0.234	

[1] MNL model including congestion. [2] MNL model excluding congestion.

The parameter estimates of the MNL model, presented in Table 5, provide more insight in the factors that explain route choice. For each variable, a reference category is chosen. For this reference category, the parameter estimate of the MNL model equals 0. The parameters of the other categories for this variable can be interpreted as the increase in log-odds of having travelled mainly on through roads (respectively distributor roads) versus access roads. For example, for trips towards home, the log of the odds of using through roads versus access roads is 0.33 lower than the log of the odds of using through roads versus access roads in the case of work trips.

To detect potential multicollinearity problems the Variance Inflation Factors (VIFs) were calculated. In general, VIFs exceeding 10 indicate the presence of serious multicollinearity undermining the validity of the results (Marquardt, 1980). Other authors consider this boundary too liberal and suggest that the variance inflation factors should not exceed 4 (Montgomory and Runger, 2003). The VIFs calculated for the model presented in this paper indicate that there was no problem of multicollinearity.

When the influence of the activity patterns is assessed, it is clear that the likelihood of taking primarily through roads is highest for work trips and lowest for leisure trips. In particular, the odds ratio of taking primarily through roads for work trips compared to leisure trips equals 1.78 (= exp(0-(-0.330))). This can be accounted for by the fact that in Flanders the longest trips made are work trips, whereas leisure activities are generally performed relatively close to the home location (Miermans et al., 2010). Another possible explanation for work trips choosing higher level roads more than other purposes, can be related to spatial location of activities.

With regard to the trip distance, the parameter estimates indicate that the longer the trip distance is, the more likely one travels on higher hierarchy roads, especially through roads. When the trip distance would increase by 1 km, the odds of travelling primarily on through roads increases 17.4 % (the odds are multiplied by 1.174 (=exp(0.160))) and the odds of travelling primarily on distributor roads increases 12.5%. Consequently, the likelihood of primarily driving on access roads decreases the longer the trip distance would be. These findings are in line with Ramming (2002), Li (2004) and Zhu (2010).

TABLE 5 Primary Road Category (MNL) Model: Parameter Estimates (Access Roads as Reference)

	Through road				Distributor road				
Parameter	**Estimate**	**S.E.**	**Chi²**	**P-value**	**Estimate**	**S.E.**	**Chi²**	**P-value**	**VIF**
Intercept	-2.355	0.446	27.958	<0.001	-3.259	0.575	32.149	<0.001	n.a.
Purpose									
- Home	-0.330	0.213	2.402	0.121	-0.879	0.277	10.031	0.002	1.864
- Work	0.000	n.a.	n.a.	n.a.	0.000	n.a.	n.a.	n.a.	n.a.
- Leisure	-0.578	0.239	5.840	0.016	-0.639	0.296	4.653	0.031	1.670
- Shopping	-0.087	0.248	0.125	0.724	-0.674	0.326	4.266	0.039	1.616
- Other	-0.175	0.240	0.532	0.466	-0.336	0.302	1.237	0.266	1.687
Distance	0.160	0.011	212.262	<0.001	0.118	0.012	93.361	<0.001	1.077
Age	0.010	0.009	1.296	0.255	0.031	0.012	7.007	0.008	2.000
Sex									
- Female	0.497	0.163	9.266	0.002	-0.714	0.246	8.452	0.004	1.227
- Male	0.000	n.a.	n.a.	n.a.	0.000	n.a.	n.a.	n.a.	n.a.
Profession									
- Blue-collar worker	0.476	0.290	2.683	0.101	0.781	0.344	5.145	0.023	1.204
- White-collar worker	0.000	n.a.	n.a.	n.a.	0.000	n.a.	n.a.	n.a.	n.a.
- Independent	0.356	0.349	1.039	0.308	0.213	0.494	0.186	0.666	1.116
- Student	0.808	0.439	3.380	0.066	-0.603	0.849	0.506	0.477	1.347
- Not professionally active	0.230	0.246	0.876	0.349	-0.492	0.338	2.121	0.145	2.168
- Other	0.316	0.321	0.965	0.326	0.632	0.413	2.342	0.126	1.238
Net personal income									
- 0-1250 €	-0.379	0.273	1.927	0.165	0.327	0.375	0.761	0.383	1.678
- 1250-1750 €	0.000	n.a.	n.a.	n.a.	0.000	n.a.	n.a.	n.a.	n.a.
- 1750-2250 €	0.003	0.196	<0.001	0.988	0.266	0.253	1.106	0.293	1.577
- 2250-2750 €	0.335	0.277	1.463	0.227	-0.582	0.460	1.598	0.206	1.443
- >2750 €	0.955	0.352	7.350	0.007	1.431	0.452	10.043	0.002	1.223
- No answer	-0.030	0.235	0.017	0.897	0.075	0.303	0.062	0.803	1.633
Geographic region									
- Antwerp	0.000	n.a.	n.a.	n.a.	0.000	n.a.	n.a.	n.a.	n.a.
- East Flanders	0.073	0.215	0.114	0.736	-0.889	0.352	6.361	0.012	1.500
- West Flanders	0.127	0.288	0.195	0.659	-0.516	0.420	1.508	0.220	1.257
- Flemish Brabant	-0.375	0.204	3.371	0.066	-0.560	0.280	4.005	0.045	1.656
- Limburg	0.428	0.210	4.159	0.041	1.358	0.248	30.112	<0.001	1.554

n.a.: standard error not available as the estimate corresponds to the reference category

Concerning the effect of the socio-demographic variables, one can observe age has a positive coefficient which means that is age increases, the likelihood of primarily driving on distributor roads increases as well. However, for through roads this coefficient is not significant. The odds of travelling primarily on distributor roads increase with 3.1% for each additional year to age of the traveller. The influence of gender is not that straightforward. On the one hand, the odds of primarily driving on through roads are 64.4% higher for females than for males. On the other hand, the odds of driving primarily on distributor roads are 49.0% lower.

With respect to profession one could notice the clear difference between students and the remaining categories. Students have the highest likelihood to drive primarily on through roads and the lowest propensity to drive on distributor routes. One of the reasons explaining the large probability of driving primarily on through roads is the fact that the large majority of these students drives by car towards the location where they participate in educational activities. Given the age of these students (18+), these locations most probably are universities or university colleges, limiting the number of possible activity locations and consequently increasing the average trip distances. In line with the results of the trip distance, thus the likelihood of primarily driving on through roads increases sharply.

Regarding the net personal income one could note that income, in accordance with distance, has an increasing effect on the likelihood of driving mainly on through roads. The odds of travelling by car on through roads are 73.7% (the odds are multiplied by 0.263 (=exp(-0.379-0.955))) lower for the lowest income class when compared to the highest income class. This clear tendency is not confirmed for distributor roads: no clear increasing or decreasing relationship is visible.

Finally, the parameter estimates also show that interprovincial differences exist. The likelihood of primarily driving on through roads is largest for Limburg and smallest for Flemish Brabant. In addition, Limburg drivers also have the largest propensity of driving on distributor roads, implying that they have the lowest propensity of driving mainly on access roads. People living in East-Flanders have the smallest probability of driving on distributor roads.

4.2 Deviations from the Shortest Path

In the second part of this study, the focus is to assess the relationship between the deviation from the shortest path and the corresponding activity-travel behaviour. In particular two relations will be investigated: the first will assess the deviation in terms of kilometres (i.e. the detour distance), whereas the second relation will express the deviation in terms of percentages of the shortest path. To estimate these relations Tobit models are developed (Tobin, 1958). These models refer to regression models in which the range of the dependent variable is constrained in some way (Amemiya, 1984). The constraint in this study is the fact that the detour distances or percentages can not be negative. The standard (Type I) Tobit model describes the relationship between a non-negative dependent variable (i.e. the detour distance of detour percentage) and a vector of in independent variables, defined by:

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases},$$

where

$$y_i^* = x_i'\beta + u_i,\ u_i \sim N\left(0, \sigma^2\right).$$

The coefficients can be interpreted in a similar way as linear regression if the interest lies on the underlying linear relationship of the whole population, as is the case in this study. Nonetheless, caution is needed when the interest lies on the effect on the expected value of the observed value. In this instance, the marginal effect can be decomposed in the effect on the expectation of fully observed values and the effect of the probability of being fully observed. The reader is referred to McDonald and Moffitt (1980) for a more elaborate discussion on the decomposition of marginal effects in Tobit models.

4.2.1 Deviations from the Shortest Path in Kilometres

First, the analyses are made for the deviation from the shortest path, expressed in kilometres. To assess the significance of the various trip-related and non-trip related predictors, a type III analysis of the effects is made, displayed in Table 6. Important to underline is the importance of the activity-based segmentation: there is a clear relationship between the deviation from the shortest path and the activities people perform. Although this relationship is not significant on the 0.95 significance level, it is significant on the 0.9 significance level and given the objectives outlined in this paper definitely worth taking into account. Next to trip-related attributes (trip distance and road type), also socio-demographic variables (age and profession) play a noticeable role.

TABLE 6 Shortest Path Deviation (Tobit) Kilometres Model: Type III Analysis of Effects

Effect	DF	Chi-Square	P-value
Road type	2	17.419	<0.001
Purpose	4	9.144	0.058
Distance	1	864.626	<0.001
Congested	1	0.828	0.363
Age	3	10.925	0.012
Gender	1	2.354	0.125
Profession	5	25.525	<0.001
Net personal income	5	11.025	0.051
Geographic region	4	6.055	0.195
Log likelihood		-2215.642	
AIC		4487.284	
McFadden R^2		0.172	

The parameter estimates of the Tobit model, presented in Table 7, provide more insight in the factors that explain the deviation from the shortest path. Again, to detect potential multicollinearity problems the Variance Inflation Factors (VIFs) are calculated. The VIFs for the model presented indicate that there is no problem of multicollinearity.

When analyzing the results concerning the influence of trip purpose, the highest deviation from the shortest path is found for leisure trips. Work trips have on average less deviation from the shortest path than leisure trips. Shopping trips have less deviation than work trips.

With regard to the trip distance, the parameter estimates indicate that the longer the trip distance is, the higher the deviation from the shortest path. The deviation from the shortest path is highest for trips that mainly use primary roads. When mainly using secondary roads, the deviation is less than when mainly using primary roads. For local roads, the deviation is less than when mainly using secondary roads. These results are probably due to the fact that one usually has to make a detour to use primary roads.

Concerning the effect of the socio-demographic variables, one can observe that if age increases, the deviation from the shortest path decreases. Older people might be less inclined to take primary roads and therefore make fewer detours. When analyzing the results with respect to profession, a clear difference between the categories is observed. Blue collar workers deviate the least from the shortest path. Trips from white collar workers have more deviation from the shortest path than blue collar workers. Independent professions deviate even more from the shortest path.

TABLE 7 Shortest Path Deviation (Tobit) Kilometres Model: Parameter Estimates

Parameter	Estimate	Standard Error	T-value	P-value	VIF
Intercept	-2.789	0.393	-7.100	<0.001	n.a.
Distance	0.134	0.005	29.406	<0.001	1.290
Road type					
-Primary (through) road	0.861	0.211	4.082	<0.001	1.403
-Secondary (distributor) road	0.658	0.290	2.268	0.023	1.234
-Local (access) road	0.000	n.a.	n.a.	n.a.	n.a.
Purpose					
-Home	0.042	0.261	0.160	0.873	1.948
-Leisure	0.641	0.286	2.242	0.025	1.702
-Shopping	-0.107	0.320	-0.334	0.739	1.655
-Other	-0.111	0.299	-0.372	0.710	1.724
-Work	0.000	n.a.	n.a.	n.a.	n.a.
Congested					
-During peak	0.165	0.181	0.913	0.361	1.057
-Off-peak	0.000	n.a.	n.a.	n.a.	n.a.
Age					
-18-25	1.053	0.457	2.303	0.021	1.880
-26-40	0.316	0.224	1.412	0.158	1.338
-41-65	0.000	n.a.	n.a.	n.a.	n.a.
-65+	-1.166	0.508	-2.294	0.022	1.271
Gender					
-Female	-0.326	0.212	-1.536	0.125	1.315
-Male	0.000	n.a.	n.a.	n.a.	n.a.
Profession					
-Blue-collar worker	-1.102	0.401	-2.745	0.006	1.255
-Independent	0.953	0.408	2.335	0.020	1.120
-Student	-0.037	0.620	-0.060	0.953	1.618
-Not professionally active	0.676	0.287	2.357	0.018	1.814
-Other	-0.560	0.397	-1.411	0.158	1.217
-White-collar worker	0.000	n.a.	n.a.	n.a.	n.a.
Income					
-0-1250 Euro	0.638	0.347	1.838	0.066	1.716
-1250-1750 Euro	0.000	n.a.	n.a.	n.a.	n.a.
-1750-2250 Euro	0.172	0.255	0.673	0.501	1.737
-2250-2750 Euro	-0.263	0.372	-0.706	0.480	1.528
-More than 2750 Euro	-0.622	0.486	-1.279	0.201	1.275
-No answer	0.543	0.297	1.826	0.068	1.744
Geographic region					
-East Flanders	0.486	0.279	1.744	0.081	1.513
-West Flanders	-0.159	0.375	-0.425	0.671	1.270
-Flemish Brabant	-0.151	0.270	-0.560	0.576	1.741
-Limburg	-0.119	0.265	-0.448	0.654	1.655
-Antwerp	0.000	n.a.	n.a.	n.a.	n.a.

n.a.: standard error not available as the estimate corresponds to the reference category

4.2.2 Deviations from the Shortest Path in Percentages

Next, the percentage of deviation from the shortest path is analyzed. Again, a Tobit model is used to estimate the relationship between the percentage of deviation from the shortest path and the corresponding activity-travel behaviour.

To assess the significance of the various trip-related and non-trip related predictors, a type III analysis of the effects is made, displayed in Table 8. There is a clear relationship between the percentage of deviation from the shortest path and the road type, the trip distance, whether or not the trip is made during peak hours, socio-demographic variables (age, gender and profession) and the geographical region (province).

TABLE 8 Shortest Path Deviation (Tobit) Percentage Model: Type III Analysis of Effects

Effect	DF	Chi-Square	P-value
Road type	2	12.5914	0.0018
Purpose	4	2.9071	0.5735
Distance	1	61.8505	<.0001
Congested	1	6.4238	0.0113
Age	3	17.1137	0.0007
Gender	1	7.579	0.0059
Profession	5	32.4271	<.0001
Net personal income	5	6.0702	0.2995
Geographic region	4	12.3039	0.0152
Log likelihood		-297.303	
AIC		650.606	
McFadden R^2		0.251	

The parameter estimates of the Tobit model, presented in Table 9, provide more insight in the factors that explain the deviation from the shortest path. To detect potential multicollinearity problems the VIFs are calculated. The VIFs for the model presented indicate that there is no problem of multicollinearity.

Trip-related attributes such as trip distance, road type and congestion have a significant influence on the percentage of deviation from the shortest path. If the trip distance increases, the deviation from the shortest path increases. The deviation from the shortest path is highest for trips that mainly use primary roads. When mainly using secondary roads, the deviation is less than when mainly using primary roads. For local roads, the deviation is less than when mainly using secondary roads. This can easily be explained by the fact that when using primary roads, mostly a detour needs to be made. During peak hours, the deviation from the shortest path is higher than during off-peak hours.

Socio-demographic factors also influence the percentage of deviation from the shortest path. If age increases, the deviation from the shortest path decreases. This means that older people make fewer detours, probably because they are less likely to take primary roads. When comparing the behaviour between male and female, the percentage of deviation from the shortest path is lower for females. Blue collar workers deviate the least from the shortest path. Trips from white collar workers have more deviation from the shortest path than blue collar workers. Independent professions deviate even more from the shortest path.

Finally, the geographic region has an impact. Trips in Flemish-Brabant have the least deviation from the shortest path, trips in Limburg have the highest deviation from the shortest path. The fact that most congestion takes place in Flemish-Brabant might make people take more local roads and thus they deviate less from the shortest path.

TABLE 9 Shortest Path Deviation (Tobit) Percentage Model: Parameter Estimates

Parameter	Estimate	Standard Error	T-value	P-value	VIF
Intercept	-0.114	0.028	-4.003	<0.001	n.a.
Distance	0.003	0.000	7.853	<0.001	1.290
Road type					
-Primary (through) road	0.053	0.015	3.500	<0.001	1.403
-Secondary (distributor) road	0.037	0.021	1.773	0.076	1.234
-Local (access) road	0.000	n.a.	n.a.	n.a.	n.a.
Purpose					
-Home	-0.006	0.019	-0.319	0.750	1.948
-Leisure	0.023	0.021	1.125	0.261	1.702
-Shopping	-0.008	0.023	-0.337	0.736	1.655
-Other	0.001	0.022	0.026	0.979	1.724
-Work	0.000	n.a.	n.a.	n.a.	n.a.
Congested					
-During peak	0.033	0.013	2.535	0.011	1.057
-Off-peak	0.000	n.a.	n.a.	n.a.	n.a.
Age					
-18-25	0.012	0.033	0.370	0.711	1.880
-26-40	0.032	0.016	1.969	0.049	1.338
-41-65	0.000	n.a.	n.a.	n.a.	n.a.
-65+	-0.132	0.037	-3.595	<0.001	1.271
Gender					
-Female	-0.042	0.015	-2.753	0.006	1.315
-Male	0.000	n.a.	n.a.	n.a.	n.a.
Profession					
-Blue-collar worker	-0.081	0.029	-2.851	0.004	1.255
-Independent	0.085	0.030	2.878	0.004	1.120
-Student	0.022	0.045	0.479	0.632	1.618
-Not professionally active	0.064	0.021	3.092	0.002	1.814
-Other	-0.019	0.028	-0.676	0.499	1.217
-White-collar worker	0.000	n.a.	n.a.	n.a.	n.a.
Income					
-0-1250 Euro	0.035	0.025	1.422	0.155	1.716
-1250-1750 Euro	0.000	n.a.	n.a.	n.a.	n.a.
-1750-2250 Euro	0.016	0.018	0.845	0.398	1.740
-2250-2750 Euro	-0.022	0.027	-0.816	0.415	1.528
-More than 2750 Euro	-0.034	0.035	-0.974	0.330	1.275
-No answer	0.020	0.021	0.913	0.361	1.744
Geographic region					
-East Flanders	0.026	0.020	1.271	0.204	1.513
-West-Flanders	-0.004	0.027	-0.153	0.878	1.270
-Flemish Brabant	-0.007	0.019	-0.368	0.713	1.741
-Limburg	0.050	0.019	2.629	0.009	1.655
-Antwerp	0.000	n.a.	n.a.	n.a.	n.a.

n.a.: standard error not available as the estimate corresponds to the reference category

If we compare the results for the two models (kilometres and percentage) analysing the deviation from the shortest path, for both models road category, distance, age and profession are significant variables. For the kilometres model, purpose is also a significant variable. For the percentage model, gender and geographic region are significant variables. The variables that are significant in both models also show the same impact on the depending variable for theses four independent variables, as can also be found in the description of the results in the previous paragraphs.

5 DISCUSSION AND CONCLUSIONS

In this study the relationships between route choice decisions (i.e. the type of roads driven by and the deviation from the shortest path), activity patterns and other influencing variables have been assessed. The results confirm the finding by Abdel-Aty and Huang (2004) that route choice is a function of multiple factors, not just travel time or distance. Crucial for modelling route choices or in general for traffic assignment procedures is the conclusion that activity patterns have a clear influence on the road category primarily driven on. Particularly, it was shown that the likelihood of taking primarily through roads is highest for work trips and lowest for leisure trips. This certainly suggests that traffic assignment procedures should be developed that explicitly take into account an activity-based segmentation. In addition, it was shown that route choices were similar during peak and off-peak periods. This supports the conclusion by Avineri and Prashker (2004) that car drivers are not necessarily utility maximizers, or that classical utility functions in the context of route choices are omitting important explanatory variables, and that further research is needed to determine whether they are prospect maximizers or whether other behavioural theories provide a more solid behavioural basis. The results in this paper also confirmed that socio-demographic variables such as age, gender, profession and income, and geographical context (i.e. province) play a noticeable role in route choice decisions. When analyzing the relationship between the deviation from the shortest path (in kilometres) and the activities people perform, a significant influence of the activity-based segmentation is found. Furthermore, in accordance with international literature, next to trip-related attributes (trip distance and road type), also socio-demographic variables (age and profession) play a noticeable role. When investigating the percentage of deviation from the shortest path, the variables road type, trip distance, whether or not the trip is made during peak hours, socio-demographic variables (age, gender and profession) and geographical region have a significant influence.

These results certainly suggest that traffic assignment procedures should be developed that explicitly take into account an activity-based segmentation. For example, different utility functions for trips with different trip purposes may be used.

A potential pathway for further investigating route choice decisions might lie in the roots of more psychological underpinnings. As documented by Parkany et al (2006) attitudes play an important role on travel decisions as they help guide behaviour, and a typology of attitudes toward route choice could be used to stratify traffic assignment models. Besides personal attitudes, also a wide variety of other explanatory variables related to route choice. Future data collection efforts concerning route choice could also incorporate additional factors including traveller-related aspects (e.g. life cycle, education, household structure, household car possession, and household driver license possession (Jan et al., 2000), road characteristics (e.g. speed limits, road with, road length, number of lanes, angularity, intersections, aesthetics (Jan et al., 2000)), traffic characteristics (e.g. traffic safety, reliability of travel times (Papinski et al., 2009)), and situational variables (e.g. weather conditions (Cools et al., 2010a, Cools et al., 2010c), holiday effects (Cools et al., 2009, Cools et al., 2010b) and traffic information (Zhang and Levinson, 2008)). Moreover, future research should extent to other transport modes such as walking, bicycle use, public transport and carpooling. Another extension to the problem could be to take uncertainty into account (e.g. Chen et al., 2012). As a last direction for further research, instead of studying the shortest path decision, it would also be interesting to study the relationship between the fastest route and the activities people perform.

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