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Using panel data for modelling duration dynamics of outdoor leisure activities

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A R T I C L E I N F O

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A B S T R A C T

This paper examines the effects of socioeconomic characteristics, trip characteristics and life events on outdoor leisure activities and leisure duration in the Netherlands, based on 14 554 observations from three waves of data from The Netherlands Mobility Panel (in Dutch: *MobiliteitsPanel Nederland*). A standard mixed logit as well as a 'zero-leisure' scaled model was estimated to cover interpersonal and intrapersonal heterogeneity, The model was estimated for weekends, weekdays, transport mode choice of the activity, and specific leisure activity.

The results show that travel time and transport mode choice for leisure trips have significant links with activity duration. Walking and cycling are dominant modes for short-duration activities and public transport for long-duration activities, and activity duration increases with travel time. The probability of short-duration leisure activities is higher on workdays. Certain life events positively affect the duration of leisure activities, whereas accessibility and bicycle ownership have no effect on leisure activity duration. The scaled model shows that the utility of any duration is about 10% larger for respondents who reported at least one day without leisure activities ('zero leisure'). Leisure activities undertaken during the same week are significantly correlated, representing significant intrapersonal variation.

The paper highlights the importance of analysing duration of activities for different activity types and days of the week and underlines the strong link of temporal (week, year) and spatial (activity type location) dimensions with transport mode choice.

1. Introduction

In transport-related research, the flexibility of outdoor leisure and recreational activities confers complexity to the demand models. The type of activity for which a journey is undertaken (such as sports or shopping) also determines the type of location (land use). In recent decades, the demand for recreational activities has increased because of increasing wealth, aging populations and changing lifestyles (Grigolon et al., 2013). It has therefore become important to analyse the expected demand for such locations, which is also associated with the duration of the undertaken activities and the transport needs of those locations. For example, the availability of parking facilities, operating times of public transport, proximity to leisure locations and connectivity by public transport can limit the duration and frequency of the leisure activities a person or family engages in.

Most non-work travel activity models focus on activity travel patterns for household interactions, recreational activities, and mode choice on holidays or weekends. Models for non-work journeys include a broad spectrum of trip purposes, such as family visits,

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shopping, as well as school- and church-related activities (Huang and Levinson, 2015). Bhat and Gossen (2004) looked at walking, jogging, riding a bicycle, and driving (touring) without having a specific destination as recreational activities. Bhat et al. (2004a) have examined how intra-household interactions influence weekday in-home and out-of-home activity generation; Habib and Hui (2015) have analysed the travel scheduling behaviour of older people for daily activities by using the framework of Bhat et al. (2004a). Arman et al. (2015) developed a model for household activity and vehicle allocation. Pozsgay and Bhat (2001) explored an attraction-end choice model of home-based urban recreational trips and Wang et al. (2015) investigated holiday travel behaviour characteristics in a trip chain. Overall, though, there is still little attention for non-work (leisure) activities.

The duration of outdoor leisure activities leads to dynamism in the transport market. Several factors influence the duration of leisure activities, such as a person's variety of activities and locations (intrapersonal variation). Studies based on longitudinal data have been conducted to analyse activity participation (Axhausen et al., 2002) and temporal and spatial variability of leisure activities (Schlich et al., 2004). These studies highlight the importance of analysing leisure traffic, and the relevance of modelling longitudinal data that covers both changing situations and sporadic behaviour.

Similarly, it is known that the mixture distributions can be discrete or continuous, and previous work show that any sample population may be decomposed into discrete segments that differ in their awareness of and proclivity towards certain mobility pattern (Vij et al., 2013). Multiple discrete continuous structures (MDC) have emerged as popular framework (Bhat, 2008), applied to goods consumption when continuous nature is involved, such as distance and time. Recently, MDC models have been extended to an integrated latent variable and choice model of time allocation (Enam et al., 2018), highlighting the importance of socioeconomic characteristics and individual's heterogeneity in activity durations. Also, some model studies treat activity type and duration as a continuous variable, e.g. multiple-discrete continuous extreme value models –MDCEV- (Calastri et al., 2017) rather than treating duration of activities as categorical manifestations. In most of the cases, this model structure assumes that individuals have a constant daily (24 h) budget of activity duration. An utility function for each (discrete) alternative is estimated and linked with the good consumption. And, a generic set of ‘consumption’ (e.g. duration) parameters is estimated.

However, individuals can have apriori preferences for a specific category of good consumption, in this case leisure activity duration (i.e. short or long duration leisure activity), depending on their preferences, activity patterns and available time budget during the day. So, longer durations do not always mean higher utilities. For example, a long duration leisure trip to an amusement park in the weekend versus a short duration lunch walk at a working day. Also, Calastri et al. (2017) indicated that consumer's preference structure might be such that she/he might not derive additional utility from additional consumption beyond a certain maximum level of consumption of a product. Exploring this required flexibility, some authors consider multiple constraints in time allocation models (Castro et al., 2012). Being flexibility a strong motivation in this paper to analyse duration of activities as categories instead of continuous variable, which allows the estimation of range-specific parameters, when an individual faces a single choice situation at the time.[1] Previous research highlighted the advantages of discretization of alternatives in choice models. For example, Antonini et al. (2006) generated discrete categories of physical space, via the discretization of the set of walking alternatives. And, Vovsha and Bradley (2004) developed a hybrid discrete-duration model with temporal resolution (discretization) of 1 h. As described in Vovsha and Bradley (2004), this model has the advantages of a discrete choice structure (the flexibility and easy to estimate and apply) and the advantages of a duration model as the parsimonious structure with a few parameters that support any level of temporal resolution including continuous time.

Furthermore, the advantages of a repeated panel data are considered here to account for individual's heterogeneity as consumer's preference via (panel effects of) a mixed logit structure, see La Paix Puello et al. (2017). None of the previous modelling studies on discrete-continuous structures of activity durations have considered long term repeated panel data.

This paper presents an analysis of the duration of out-of-home leisure activities as discrete choice categories. The objective of our study was to investigate the factors that affect duration of outdoor leisure activities in a medium-term perspective (3 years). We explore shopping, sports/hobbies, tourism, walking, and other leisure activities and we took three years of data from The Netherlands Mobility Panel (MPN) to conduct the analysis on. The novelty in this paper comes from both the applied method as the characteristics of the data used. This paper develops an extended mixed logit modelling framework which uses discrete measurements of activity durations to disentangle range-specific effects of the estimated parameters, and a scale parameter of ‘zero-leisure days’ to incorporate temporal interdependencies between activities. Furthermore, we use data from the MPN, a unique panel data set in size (currently the largest ongoing mobility panel in the world) and scope (a very rich set of variables). This allows estimations of the effects of socioeconomic characteristics, trip characteristics and life events on outdoor leisure activities and leisure duration, and incorporation of interpersonal and intrapersonal variations in leisure activities and duration over time.

The remainder of this paper is organised as follows. Section 2 introduces the databases that were used for trip characteristics, socioeconomic characteristics, life events and other variables. Section 3 discusses the model setup (setup of alternatives, specification of variables, and conceptual model). Section 4 explores the statistics of the respondents and the variables collected from the database. Section 5 discusses the model results and Section 6 highlights the main findings of our study and provides recommendations for future work.

2. Literature on modelling duration of leisure activities

Activity duration has many effects on travel patterns for out-of-home activities. One effect is that the duration of the main activity can

[1] It means that the decision process is faced towards the duration of the activity, instead of the type of activity to be undertaken. By definition, different types of leisure activities are not considered as a choice set, e.g. transport modes in mode choice, given the unrelated nature of the activities (e.g. shopping vs sports).

affect the propensity to undertake a secondary trip (Shiftan and Ben-Akiva, 2011). For instance, when the duration of a particular activity is long and is considered the primary/main activity (Katoshevski et al., 2015), there may not be any secondary trip. On the other hand, shorter periods of activity can be followed by one or more secondary trips towards different activities. And, undertaking no leisure activities at all on specific days may affect the duration of leisure activities undertaken on the other days (or vice versa). It means that, even when time budgets are fixed (e.g. 24 hrs each day), the duration of activities implies a temporal (e.g. week) correlation that should not be overlooked.

Both frequency and duration of leisure activities are linked to many factors. They are related to other activities undertaken during the day, the nature of the place of the activity, workload of the day, travel time to the location of the activity, its accessibility, people's socioeconomic characteristics and day of the week. Particularly, socioeconomic characteristics are important explanatory variables of time and expenditure in leisure activities. For example, people younger than 18 years of age compensate spending less money with spending more time on outdoor recreation, whereas being part of the middle class has a negative effect on the duration of recreational activities but a positive effect on expenditure for activities related to wellness and going out (Dane et al., 2014). Deserpa (1971) developed the fundaments of economic value of time, as unit of googs, and the value of each singular unit. Based on this, more recently, Jara-Díaz et al. (2008) analysed the value of leisure with econometrically estimated parameters in three diverse settings (Switzerland, Germany and Chile), and found that value of leisure varies by wage. The individual has to earn an income that requires time assigned to work, and this assignment is not only dependent on the money reward but also on the satisfaction (or dissatisfaction) that work causes. Then, value of leisure activities can be related to several latent effects. But, category-specific effects of a variety of elements (e.g. spatial, temporal and individual) in activity durations have not been approached so far.

Other characteristics, such as presence of kids at home, engaging in recreational activities in the morning, and certain types of activities (e.g. visiting someone) have a positive effect on time spent on leisure activities. Also, social activity duration can be longer for people with more cars and people who work full-time (Habib et al., 2008). Bhat and Gossen (2004) modelled pure recreational activities of individuals during the weekend, including in-home and out-of-home activities. They found different patterns of out-of-home and in-home leisure activities for both temporal (e.g. weekends or weekdays) and socioeconomic characteristics. Longer trips are related to expectations based on provided information (e.g. internet) as well as on certain components of variety-seeking (Arentze and Timmermans, 2005). Previous studies have identified that the variety of leisure is quite high, making variety-seeking an important factor of human behaviour for recreational and leisure activities; see for example the work by Schlich et al. (2004). However, the extent to which those effects can be captured through dynamics of longitudinal data is still unclear.

Recently, the dynamics of the personal network, activity needs and travel requirements in response to life events have been explored (Sharmeen et al., 2014). It turned out that activity needs are significantly influenced by life events such as starting university, moving home, or a change in work hours. Life events have a vital role in the timing of certain mobility decisions (e.g. car ownership and commute mode change), so ignoring these issues may lead to biased travel demand models (Oakil, 2013). Furthermore, Clark et al. (2016) found that changes in commuting behaviour are strongly influenced by life-events, spatial context and environmental attitude. And, Chatterjee et al. (2013) found that life events are usually triggers for cycling as transport mode, but external changes to the bicycle environment play an important role as well. However, the specific effect of life events in duration of leisure activities, linked to activity mode choice, has not been disentangled yet.

With the advent of the activity-based modelling approach, the use of panel data has been emerging since the late 1980s (Cherchi and Cirillo, 2008). Most of the panel data used for transport choice modelling are multi-week panel data (Cherchi et al., 2009; Cherchi and Cirillo, 2008; Jara-Diaz et al., 2007; Cirillo and Axhausen, 2010; Schlich and Axhausen, 2003). Social activity duration has been mostly analysed based on cross-sectional data (van den Berg et al., 2012) and both time and expenditure for leisure activities during a week have been analysed via simultaneous models (Dane et al., 2014). It means that little attention has been allocated so far towards analysing the dynamics of leisure activities with longitudinal patterns. By analysing longitudinal data, more precise information of the dynamics and changes in individual mobility can be explored. Specific activities have been analysed with multi-week data. For example, Bhat et al. (2004b) studied intershopping duration and highlighted strong weekly trends. Additionally, their results indicate the strong influence of individual and spousal employment-related attributes, the transport mode used for shopping, and trip-chaining behaviour on shopping frequency. However, they did not look at any links between changes in accessibility, preferred transport modes, spatial variables and duration of leisure activities.

This work in this paper contributes to the literature by analysing panel data on leisure activities and duration, incorporating a wide range of explanatory variables to explain intra- and interpersonal variation in leisure duration, including travel-related variables, life events and socioeconomic characteristics.

3. Description of The Netherlands mobility panel' (MPN)

The Netherlands Mobility Panel (in Dutch: *MobiliteitsPanel Nederland*, abbreviated as MPN) – a state-of-the-art household panel – aims to describe the dynamics in travel behaviour of individuals and households over time. The MPN is designed and implemented to understand social trends and their impacts on travel behaviour on an aggregated level, to identify and explain day-to-day variations in mobility, and look at the role of habits in travel behaviour (Hoogendoorn-Lanser et al., 2015). As an inherent feature of panel data, the MPN survey overcomes the limitation of cross-sectional travel surveys, in which only one day is surveyed for each respondent.

The MPN collects yearly travel data of about 2000 households with 4000 individuals since 2013. MPN collects data with various research instruments (questionnaires and travel diary) and complementary data is added from administrative registers. Before the start of the MPN, in 2013, a screening questionnaire was conducted among 9000 contact persons (gatekeepers) from the Dutch TNS NIPO panel to ask their willingness to participate and collect travel data for non-response analysis. Household contact persons are asked, once a year in autumn (Sept–Nov) to fill in a household survey with questions on the household characteristics such as the composition, socio-economic characteristics and vehicle ownership and details (e.g., license plate number, annual mileage). One week after the household survey, all household members aged 12 and older, are asked to participate in an individual survey comprising questions on individual characteristics such as age, income, ethnicity, working hours, mode preferences, access and use of internet facilities. Twee weeks after the individual survey, all respondents (ages 12 years and older) are asked to keep a three-day online trip diary for three successive days (including weekend days), and the selection of days is kept for successive waves. Randomization is used to get a good distribution of respondents by days of the week. Data is collected at the trip level, defined as a one-way course of travel from an origin to a destination with a single main purpose, which can comprise different stages linked to a change of mode.

The MPN travel diary is a place-based diary, which can be interpreted as a hybrid of activity-based and trip-based diaries. The rationale behind both the activity-based and location-based diaries is that respondents are better at remembering their activities or visited locations than they are at recalling all of their trips (Hoogendoorn-Lanser et al., 2015). The web-based diary is a day planner and developed as a two-level webpage: at the higher level, respondents fill in locations, activities, arrival and departure times, while on the lower level page they report detailed information about trips and trip stages. The day planner is completed from 00:00 until 23:59, ensuring a complete overview of activities, trips and travel times. This also makes the MPN an appropriate data set to examine activity-based travel patterns, including tradeoffs between leisure trip length and activity durations.

MPN data is unique because of the sample size of the panel but also the scope of the survey. It collects many different data for the same person in each wave for consecutive years It contains individual and household socioeconomic characteristics, life events, perceived neighbourhood accessibility, preferences for transport modes, travel data for work and non-work (i.e., leisure) activities etc. on a longitudinal basis, which enables measuring changes over time. Furthermore, the MPN is enriched with data from registers, such as car characteristics, built environment and socio-economic variables at neighbourhood level. Travel distances and times for non-chosen modes are added using dedicated trip planners.

For more details about the MPN survey methodology we refer to Hoogendoorn-Lanser et al. (2015) and Olde Kalter and Geurs (2016). In our study, we used the three waves 2013, 2014 and 2015 (which were all the available waves at the time of the study; more waves have since become available). In this paper, we selected the data from 1805 individuals who had participated in the survey for three years and completed the three-day trip diary (i.e. the 'stayers'). We focus on the stayers as this allows an analysis of intrapersonal variation in addition to interpersonal variation in leisure activities.

As non-work activities, the MPN considers trips to pick up people or goods, shopping trips (including groceries), tours (including walking), hobbies (including sports), and other leisure activities. In-home leisure activities (including visiting friends, relatives or health facilities) are not part of this analysis.

3.1. *Descriptive statistics*

As mentioned, the MPN data consists of 3-day trip diaries of individuals. Details about the trips and activities are collected along with the exact time of start/arrival and end/departure. The activity durations of the activities are created by subtracting the arrival time for a particular activity from the departure time, as follows: *Activity duration = departure time from 'x' – arrival time at 'x'*.

The categories of leisure activity duration were selected based on the statistical distribution of activity duration per trip. In the MPN, 25% of the leisure activities take 20 min or less, 50% of activity duration are 75 min or less, 75% of activities are 192 min or less and 95% of activity durations fall within 525 min duration time. Additionally, we carried out empirical tests to determine the most statistically significant duration categories. Based on those tests and the statistical distribution, we divided the activity duration into four groups, as follows: (1) up to 20 min; (2) 21–75 min (~1 h); (3) 76–192 min; (4) more than 192 min (~3 h).[2]

Tables 1 and 2 show the descriptive statistics of our sample, as percentages per population segment. Table 1 contains socioeconomic characteristic, whereas Table 2 lists travel-related details. When analysing the socioeconomic characteristics, gender differences reveal themselves as not substantial; age differences are more relevant. For example, elderly people tend to undertake shorter leisure and recreational activities than teenagers. We can also observe that levels of individual income have relatively little effect on activity duration, although persons in low-income households have a higher tendency towards activities up to one hour duration. When an individual's household composition changes (e.g. single to couple), it also has effects on the duration of leisure activities. For instance, single persons tend to have more short-duration activities than couples and couples with children. Surprisingly, being employed has little effect on the duration of outdoor activities (with the exception of durations of longer than 192 min).

Table 2 lists the travel-related and preference variables and shows that both trip purpose and transport mode can make a difference in the duration of activities; this provided the motivation for estimating additional models for trip purpose and mode choice (see Section 4). The activities we considered are grouped into the following categories in the MPN data: shopping (49%), tours and walking (11%), sports and hobbies (20%), and other leisure activities (20%). 91% of the shopping activities are short-duration (up to 75 min), whereas other activities have larger percentages for longer durations – tours and walking (57%), sports and hobbies (73%) and other leisure activities (62%). Table 2 shows that there is a high tendency (34%) to undertake short-duration leisure and recreational activities in the late afternoon, whereas the probability of those activities taking place during the night is low (22%), as expected. Travel time can influence the duration of activities as well and, as Table 2 also confirms, most people do have a tendency towards long-duration leisure activities during weekends, while they usually have short leisure activities on workdays. These data do not show do not show substantial

[2] We systematically applied different thresholds and estimated the models. We chose the threshold that had the best goodness of fit, which in this case was given by the percentiles.

Table 1
Descriptive statistics of the individual and household SE Variables MPN data for stayers.

		Variables	01-20 min (%)	21-75 min (%)	76-192 min (%)	>192 min (%)	% in the reported sample
Individual characteristics	Gender	Female	25	31	28	16	55
		Male	25	30	28	17	45
	Age (years)	Teen *(12–17)*	17	30	37	16	5
		Young *(18–39)*	25	30	29	16	30
		Aged *(40–65)*	25	32	28	16	47
		Elderly *(>65)*	26	31	27	16	25
	Education	Uneducated	10	33	39	18	2
		Basic education	22	32	33	13	6
		Intermediate education	25	31	28	16	82
		Higher education	25	30	29	17	13
	Employment status	Employed	25	31	29	15	55
		Retired	25	31	27	17	26
		Others	25	31	28	16	32
	Personal Income	No income	22	31	32	15	11
		Low income *(<1500€)*	26	30	28	16	36
		Medium income *(1501–2500€)*	24	31	29	16	35
		Moderate Income *(2501–3500€)*	27	30	28	16	11
		High income *(>3500€)*	23	31	32	14	2
		Private car ownership	25	31	28	16	75
		No out-of-home work	25	32	28	15	47
Household characteristics	Household Income	Low *(<26200€)*	26	31	27	17	21
		Medium *(26200–65000€)*	25	31	29	15	53
		High *(>65000€)*	22	31	30	17	19
	Household Composition	Single	26	30	27	16	31
		Couple	25	31	28	16	39
		Couple with child	23	32	30	16	31
		Single parent	24	32	30	14	4
		Household car ownership	24	31	28	16	86

differences in activity duration in response to reported life events and between the different waves. In summary, the descriptive statistics show which are the most relevant variables to be included in the model (see Section 4).

3.2. *Zero-leisure days*

In the MPN trip diary, each person has a personal 3-day trip record with a combination of workdays and weekends. While analysing the leisure and recreational activities, we found that some days did not include any leisure activity at all; referred to as 'zero-leisure days'. Around 34% of all days did not have any leisure activities; 27% of these instances concern workdays while 7% are in the weekends. This reflects that respondents have more leisure trips during the weekend than on workdays.

4. Analytical framework

4.1. *Model structure*

Discrete continuous model structures have been used to represent activity duration (Bhat, 2005) and joint models (see for example Srinivasan and Bhat (2006)) as well as mixed multinomial logit functions have been applied for e.g. out-of-home recreational episodes (Bhat and Lockwood, 2004). However, activity duration as categorical variable has received less attention, whereas this structure allows measuring the intrapersonal dynamics of activity duration via error components. The main advantage of using a mixed ordinal structure lies in having an alternative-specific setup for both respondent heterogeneity and estimated parameters (range-specific or alternative specific parameters).[3]

In the family of logit models, the mixed logit (ML) is considered highly flexible for estimating any random utility model. The ML is one of the most powerful (logit) models as it overcomes the three major limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2003). In addition, since a panel

[3] The largest duration is set as base because it is the least preferred, which makes the interpretation more straight forward.

Table 2
Descriptive statistics of travel-related and preferences variables in MPN data for stayers (in percentages of total row).[1]

	Variables	01-20 min (%)	21-75 min (%)	76-192 min (%)	>192 min (%)	% in the reported sample
Travel related						
Trip purpose	Shopping	44	47	8	1	49
	Sports, hobby	6	21	57	16	20
	Tours, walking	21	22	25	32	11
	Leisure	13	24	45	17	20
Mode choice to activity	Car	22	37	31	10	41
	Public Transport (PT)	27	19	33	21	3
	Bicycle	31	35	27	6	30
	Walk	33	30	22	16	25
Departure time	Early morning (7–9)	21	26	29	24	7
	Late morning (9–12)	26	38	25	11	29
	Early afternoon (12–14)	29	34	27	11	19
	Late afternoon (14–17)	34	41	19	6	25
	Evening (17–20)	23	23	41	14	17
	Night (20–24)	22	23	51	4	2
	Midnight to dawn (24–4)	30	30	17	23	1
Travel time	0-20 min	31	38	24	7	72
	21-60 min	17	26	36	20	22
	61-120 min	21	21	32	26	5
	over 121 min	27	25	23	25	2
Others						
Frequency of using mode (>=4 days/week)	Car	24	32	29	16	42
	PT	23	28	35	15	4
	Bicycle	25	31	28	16	40
	Others	24	29	28	18	8
Preferred mode for going-out	Car	25	31	29	15	33
	Bicycle	25	32	29	14	24
	PT	23	32	28	17	9
	Walk	24	33	29	15	5
	Other combination	25	31	29	15	16
Preferred mode for shopping	Car	25	33	28	15	31
	Bicycle	25	31	29	15	29
	PT	25	32	29	14	8
	Walk	26	30	30	15	8
	Other combination	26	33	26	14	20
Internet usage (4 days/week)	Social networking	24	31	29	16	22
	Entertainment	25	30	29	15	11
	Office work	24	31	29	16	15
	Online shopping	24	32	32	10	2
Life Events	Change in job address	26	33	28	13	10
	Change in job schedule	25	33	28	14	13
	Move together	28	37	25	9	2
	Death in HH	24	38	29	9	1
Stated change	Getting a job	25	32	28	15	4
	Moving together	20	43	30	7	0
Weekday	Workday	30	35	25	10	70
	Weekend	22	32	33	13	30
Wave	2013	20	24	19	8	35
	2014	18	24	19	8	33
	2015	19	23	19	8	32
Variety seeking	1	27	38	24	12	5
	2	25	34	29	12	20
	3	26	35	28	11	32
	4	29	34	27	11	26
	5	33	33	25	9	12
	6	33	31	28	8	4
	7	33	22	29	15	1
	8	57	14	29	0	0

[1] Values are calculated based on three waves of data.

database includes repeated observations, the use of mixed multinomial logit is appropriate for panel data because it accounts for correlation among observations belonging to the same individual (Yáñez et al., 2011). See for example the paper by Train (2003) for more information about the functional form of the ML. Also, a competition structure operates at the individual level and not at the choice occasion level (see Bhat and Lockwood (2004)).

We used the mixed logit model to analyse the sensitivity and dynamics of the independent variables towards duration of leisure activities. Fig. 1 shows the conceptual model framework; a set of explanatory variables will be tested, with error components for panel effects and two scale group parameters for zero-leisure days. The following subsections describe how we set up the alternatives and variable specifications.

Since this study used the MPN panel database, we applied error components to explore individuals' sensitivity. Error components simply create correlations among the utilities for different alternatives. According to Train (2003), the utility faced by respondent n in relation to the alternative j can be expressed as:

$$U_{nj} = \alpha' x_{nj} + \mu'_n z_{nj} + \varepsilon_{nj} \tag{1}$$

Here, x_{nj} and z_{nj} are vectors of observed variables relating to alternative j, α is a vector of fixed coefficients, μ is a vector of random terms with mean zero, and ε_{nj} is iid (independent and identically distributed) extreme value. The terms in z_{nj} are error components that, along with ε_{nj}, define the stochastic portion of utility. For this study, the unobserved utility can be defined as ω_{nj}, which will be correlated with

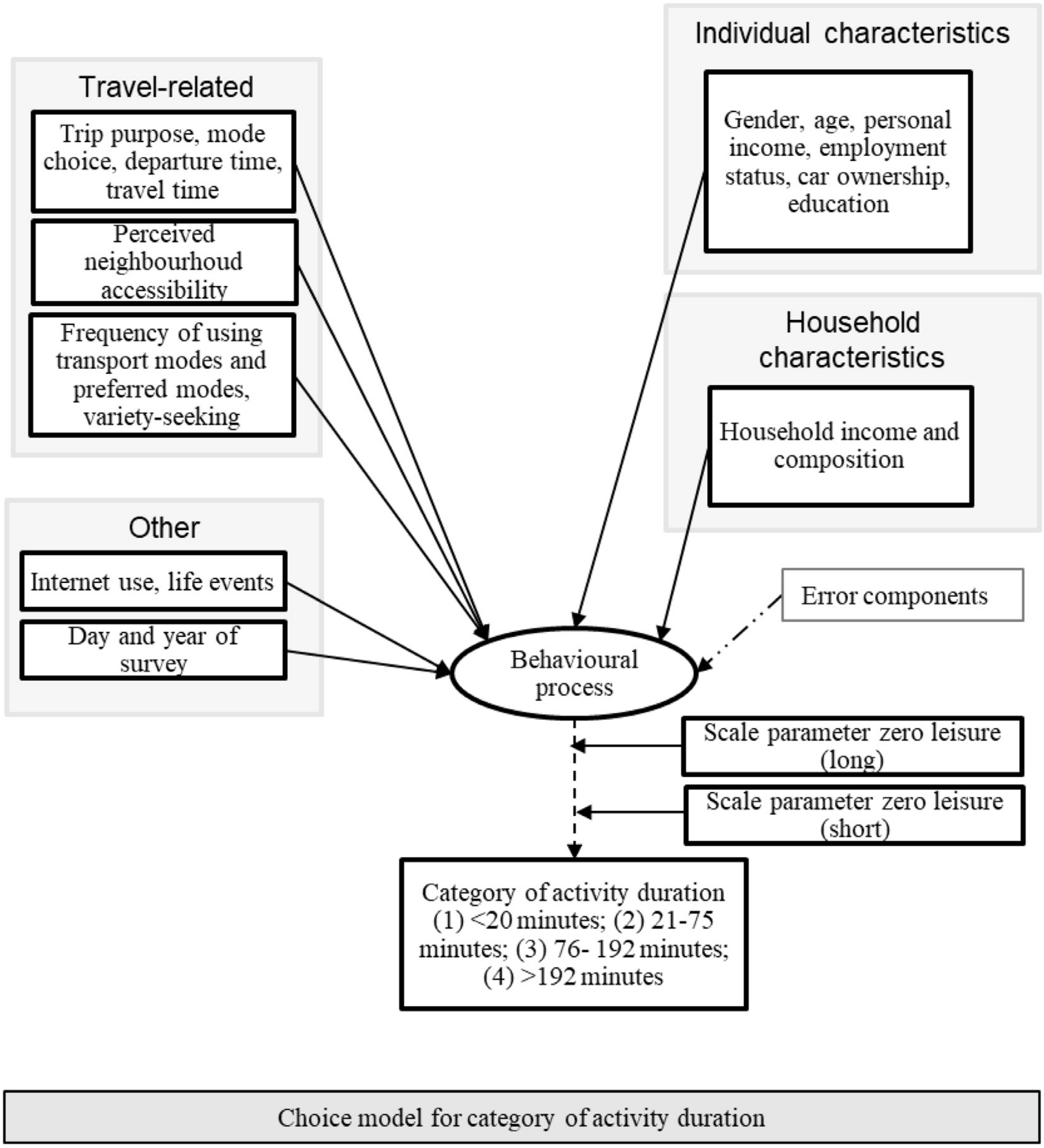

Fig. 1. Conceptual model for leisure and recreational activity duration.

person ID and empirically depends on the specifications of z_{nj}. Thus, $\omega_{nj} = \mu'_n z_{nj} + \varepsilon_{nj}$. For standard logit, there is no correlation in utility over alternatives, so z_{nj} is identical to zero, such that there is correlation in utility over alternatives chosen by the same respondent.

The utility can be rewritten as:

$$U_{nj} = \alpha' x_{nj} + \omega_{nj} \tag{2}$$

In this equation, x_{nj} are the level of variables that vary among n individuals, j alternatives ((1) <20 min; (2) 21–75 min; (3) 76–192 min; (4) > 192 min). The error term with mean zero and standard deviation σ_ω is expressed as ω_{nj}, which is estimated over the observed data distribution. The unconditional probability is the integral of this product of logit formulas, one for each time period, over all values of ω.

To develop the scaled model, a group parameter ϕ_k is estimated for one of the two groups of recorded trips per day: with leisure activities (K_1) and without leisure activities (K_2 - *zero* leisure). Two different scale parameters λ_k are connected with short duration and long duration of activities in order to account for these specific scales. λ_k captures the heterogeneity among different groups k $(k_1, k_2, \ldots k_t)$ of respondents; see for example Hess et al. (2009). At the same time, the specification allows measuring the correlation within respondents (intrapersonal variation), since it accounts for the activities undertaken during the day at individual level over different weeks and waves of data collection. The utility function is now written as:

$$\lambda_k U_{nj} = \lambda_k \left(\beta x_{nj} + \omega_{nj}\right) \tag{3}$$

Here,

$$\lambda_k = \phi_{k1} K_1 + \phi_{k2} K_2 \tag{4}$$

For identification purposes, the ϕ_k parameter of one of the groups is normalised to one, and one ϕ_k is estimated. Therefore, the parameter obtained should be statistically different to 1. Two scale parameters are specified for short duration (alternatives 1 and 2) and long duration (alternatives 3 and 4). The likelihood can be written as:

$$LL\,(\Omega_\omega) = \sum_{n=1}^{N} ln \left(\int_\omega \prod_{t=1}^{T_n} P_{ni}(\lambda_k U_{nt}) f\left(\omega|\Omega_\omega\right) d\omega \right) \tag{5}$$

The calibration of this model on choice data produces estimates of the vectors of parameters Ω_ω. To estimate the mixed logit models, simulation methods are typically used. The number of draws to use is a trade-off between computational time and accuracy (Hensher and Greene, 2002). We used the BIOGEME extended software package (Bierlaire, 2003) to estimate the models, as presented in Section 5.

4.2. Specification of variables

4.2.1. Socioeconomic characteristics

Individuals' socioeconomic characteristics and household characteristics affect trip characteristics as well as activity characteristics. Therefore, along with other transport-oriented variables, socioeconomic characteristics are important in activity-based modelling (e.g. Clifton et al. (2016), Li et al. (2016), Sadhu and Tiwari (2016), Arman et al. (2015), Huang and Levinson (2015), Yasmin et al. (2015), Sharmeen et al. (2014), Srinivasan and Bhat (2005), Bhat and Gossen (2004), Pozsgay and Bhat (2001), Bhat et al. (2004b)). In this study, we consider age, gender, personal income, car driving license, car ownership, employment status an educational status.

Also, annual household income, household car ownership, residential location, household allocation (single, couple, couple with child, single parent, other). are taken into account as household characteristics. Private vehicle ownership and license are considered an individual's mobility variables.

4.2.2. Travel-related variables

Among the travel-related variables we consider: travel time to the activity (per trip), departure time, mode choice, trip purpose, and the preferred transport modes for different types of activities (going out, shopping and others). The main motivation to select these variables relies on the literature review. Travel time is one of many attributes of an activity (Mcnally and Rindt, 2007), which is also highlighted in activity based modelling (Li et al., 2016; Pawlak et al., 2015; Arentze and Timmermans, 2005). In addition, mode choice is another inherent trip characteristic for transport modelling (e.g. Li et al. (2016), Pawlak et al. (2015)). And, departure time of the day has been previously encountered as an important factor in activity schedules (Bhat and Gossen, 2004). The departure time of the day is specified as early morning (7–9am), late morning (9am-noon), early afternoon (noon-2pm), late afternoon (2–5pm), evening (5–8pm), night (8pm-midnight) and midnight to dawn (12-4am).

Perceived neighbourhood accessibility and other lifestyle factors, such as internet use are obtained from the MPN survey and also considered in the model estimation. Furthermore, a component of variety seeking is included as number of different (leisure and non-leisure) activities performed per individual within a week per year of survey. Activity duration is measured for the activities undertaken during weeks and waves of the data collection. In order to represent 'budget', we introduce the term of 'variety seeking', which means the number of different activities undertaken during a day by a single respondent. Additional models are estimated by activity purpose and transport mode, wave and for identification purposes, the corresponding parameters are excluded according to each case.

4.2.3. Other influencing factors

As described in the literature, life events are shown to be relevant for predicting activity behaviour, see for example Chatterjee et al. (2013) and Sharmeen et al. (2014). Along with the transport oriented data and socioeconomic data, the MPN database has the records for the life events of the individuals for consecutive years. Life events (e.g. graduation, employment, having a child and break up) are also included in the model specifications. We also included 'other' variables such as an individual's working hours (over and less than 20 h, not employed), internet usage per day (over 4 h/day), internet usage for online buying and selling (over 4 days/week), preferred mode for leisure activity and frequency of using different modes (over 4 days/week). Saturday and Sunday are considered the weekend, while we counted the remaining days as workdays.

5. Model estimation

Using the MPN data, we applied the discrete choice modelling approach to test the sensitivity of the attributes (travel oriented, socioeconomic) and life events for the duration of leisure activities. (See Section 3 for the definitions and descriptions of the categories of the alternatives.) We measured alternative-specific constants (ASCs) of the alternatives, assuming the highest duration (over 200 min) as a reference; this means that all ASCs are estimated except one. Different model specifications were tested and the final models were chosen based on a robust *t*-test and overall goodness-of-fit measure.

In the mixed logit, we used specific error components for each alternative that are correlated with the household ID to observe the panel effects. As can be seen in Table 3, the error components are statistically significant, indicating the household and individual correlations when undertaking leisure activities. Consistent with Jara-Díaz et al. (2008) who found that not only socioeconomic characteristics but also unobservable elements influence leisure duration (e.g. satisfaction and insecurity with job). Alternative 4 is considered the reference. Afterwards, a scaled model was estimated to find out the impact of zero leisure – when no leisure activities are performed. Therefore, two types of models were estimated on the basis of two different datasets: 1) the base model (BM) for non-work activity data only and 2) the scaled model (SM) for non-work as well as work-related activity data.

In the scaled model, the groups are based on the activities performed during the day. For instance, if the day has no outdoor leisure activity, the day is considered a 'zero-leisure' day. On the other hand, a single leisure activity defines the day as 'with leisure'. The model specification from the BM was used for the SM, which was estimated with 250 draws. As expected, the BM for only leisure data performs better than the SM, given the selection of only leisure activities. The adjusted rho square is 0.32, while the rho square for the SM is 0.20. Table 3 presents the results of the base models and the scaled models.

5.1. Leisure activity base model (BM)

Analysing the results for the base model for leisure activities, we can see that the estimated values for the alternative-specific constants (ASCs) show that – if the rest remains constant – the most preferred duration for leisure activities is around 1 h (21–75 min, alternative 2), although activities with a very short (alternative 1, 20 min) or long duration (76–192 min, alternative 3) are also very likely to be undertaken. This result is consistent with findings by Charypar and Nagel (2005), who noted that an average leisure activity duration of 2 h is unlikely; people like to have outdoor leisure activities of a very long duration or of a very short one. The model estimation shows reasonable signs for all the explanatory variables and they are statistically significant in at least one of the models, within a 90% confidence interval.

5.1.1. Effects of socioeconomic characteristics

We tested a number of socioeconomic variables. Only gender, age, educational status, employment status, out-of-home working hours, personal and household income, personal and household car ownership and household composition are found to be significant in the model specification and were therefore kept in the final specification. Females have a higher propensity to perform long-duration outdoor leisure activities. By contrast, elderly people are found more likely to spend less time on outdoor leisure activities, while young people have a tendency towards longer duration, consistent with the results of Bhat and Gossen (2004). Personal car ownership was negatively associated with long-duration recreational activities. Also, employed persons were found to be more likely to engage in shorter outdoor leisure activities.

The coefficient of zero personal income was not found significant for leisure activities specifically, but it is significant for the duration of all kinds of activities (general model). Furthermore, high household income increases the demand for long-duration leisure activities, which is also what Grigolon et al. (2013) found. Finally, individuals having a personal car are less likely to undertake long-duration outdoor leisure activities.

5.1.2. Travel-related variables

The coefficient of activities indicates that shopping is usually a short-duration activity, whereas tours and walking are not likely to be of a short duration. Moreover, engagement in sports and hobbies, and other leisure activities (e.g. going out) are also highly likely to take up larger time slots. This is quite consistent with what was found in similar studies (Grigolon et al., 2013). As expected, travel by car and bicycle are the dominant modes for outdoor leisure activities. However, for short-duration activities, bicycles are more often used than cars and cars are more likely to be used for activities that take longer. Along with the car, public transport is the most used transport mode for leisure activities of a long duration.

The leisure activities people undertake tend to be of a longer duration if they have a longer travel time (20 min or longer). Also, the departure time is also a significant parameter for leisure activities. For example, if someone wants to go out for a leisure activity of a long

Table 3
Model results.

		Only leisure		All activities scaled		2013		2014		2015		Bicycle		PT	
		Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test
	ASC Alternative 1 < 20 min (short)	1.24	**9.32**	1.63	**19.59**	1.39	**5.94**	1.55	**6.78**	0.79	**3.33**	1.46	**4.83**	1.97	**2.68**
	ASC Alternative 2 21–75 min (short)	1.25	**10.39**	1.56	**16.21**	1.35	**6.56**	1.53	**7.41**	0.86	**3.94**	1.49	**5.07**	1.58	**2.08**
	ASC Alternative 3 76–192 min (long)	1.59	**10.14**	−0.57	**−9.18**	1.78	**6.62**	1.40	**5.30**	1.47	**4.91**	2.22	**5.47**	2.55	**3.05**
	ASC Alternative 4 > 192 min (long)	Ref													
Individual Characterisitics	Gender – Female (long)	0.38	**7.01**	0.16	**5.13**	0.38	**4.04**	0.39	**4.20**	0.38	**3.86**	0.25	**2.29**	0.52	1.26
	Age – Young (long)	0.13	**1.86**	−0.40	**−9.35**	0.17	1.44	0.16	1.35	0.05	0.41	0.17	1.31	−0.29	−0.56
	Age – Elderly (short)			0.25	**6.03**										
	Employment status – Employed (short)	0.22	**3.69**	−0.25	**−6.71**	0.20	**1.94**	0.11	1.11	0.37	**3.46**	0.35	**3.01**	−0.35	−0.79
	Personal income – No income (short)			−0.24	**−3.71**										
	Private car ownership (long)	−0.18	**−2.61**			−0.16	−1.30	0.01	0.11	−0.33	**−2.70**				
Household Characterisitics	Household income – Low (long)	−0.14	**−1.85**							−0.22	**−1.64**	−0.16	−1.18		
	Household composition – Couple (short)			−0.15	**−3.61**										
	Household car ownership (short)	−0.41	**−6.07**			−0.48	**−3.76**	−0.52	**−4.34**	−0.27	**−2.44**	−0.11	−1.09		
Travel related															
Trip purpose	Shopping (short)	3.07	**42.69**	2.29	**44.55**	2.98	**24.55**	2.92	**23.78**	3.36	**25.50**	3.76	**24.49**	1.83	**3.51**
	Sports, hobbies (long)	0.59	**8.64**	1.19	**21.94**	0.48	**4.06**	0.76	**6.54**	0.55	**4.44**	0.35	**2.77**	1.60	**2.82**
	Tours, walking (short)	0.22	**2.43**	0.70	**14.12**	0.44	**2.93**	−0.07	−0.46	0.31	**1.87**	1.04	**4.10**	1.09	0.96
Mode choice to activity	Car (long)	0.68	**9.62**	7.38	**2.43**	0.56	**4.70**	0.81	**6.66**	0.71	**5.51**				
	Car (short)			7.36	**2.42**										
	Public transport (PT) (long)	0.66	**4.29**			0.78	**3.07**	0.85	**3.25**	0.30	1.02				
	Bicycle (long, alt. 3)	0.59	**5.98**			0.68	**3.92**	0.73	**4.15**	0.41	**2.32**				
	Late morning (short)			7.75	**1.88**										
	Early afternoon (long)	0.28	**4.04**	−0.87	**−17.49**	0.27	**2.35**	0.22	**1.87**	0.36	**2.84**				
	Late afternoon (short)	0.55	**8.26**	1.52	**31.29**	0.49	**4.33**	0.63	**5.55**	0.55	**4.51**	0.54	**3.96**	1.40	**2.73**
	Evening (long)	0.39	**5.45**	−0.77	**−13.56**	0.43	**3.56**	0.32	**2.59**	0.42	**3.21**				
	Evening (short)			0.15	**2.90**										
	Night (long)	2.15	**5.83**	−1.36	**−14.13**			1.09	**2.39**	2.61	**3.25**	2.36	**2.79**		
	Night (short)	1.89	**5.03**					0.87	**1.84**	2.59	**3.19**	1.71	**1.98**		
Travel time	0-20 min (long)	1.52	**11.92**	3.99	**41.02**	1.26	**6.08**	1.43	**6.67**	2.09	**8.09**	1.70	**4.66**	3.87	**2.14**
	0-20 min (short)	1.37	**16.16**	2.97	**32.08**	1.25	**8.77**	1.27	**8.65**	1.65	**10.38**	0.92	**4.21**	4.86	**2.85**
	20-60 min (long)	0.86	**6.88**			0.72	**3.53**	0.84	**3.96**	1.17	**4.67**	1.31	**3.54**	1.34	**2.26**
	20-60 min (short)			4.08	**36.55**										
	60-120 min (long)	0.44	**3.19**			0.78	**3.36**	0.40	**1.71**						
	Variety seeking (alt. 4)	−0.24	**3.77**	−0.22	**−12.03**	−0.33	**7.24**	−0.30	**6.63**	−0.34	**7.29**	−0.33	**5.42**	−0.35	**1.78**
Other factors															
	Frequency of using mode – PT (short)	0.28	1.47			0.37	1.05	0.20	0.62	0.23	0.65	0.84	**2.04**		
	Life events – Change job (long)	0.48	**2.23**							0.59	**1.96**	0.62	1.38		
	Weekday – Workday (short)	0.42	**7.29**	0.30	**7.87**	0.39	**3.99**	0.31	**3.20**	0.61	**5.73**	0.45	**3.76**	1.49	**3.06**

(*continued on next page*)

Table 3 (*continued*)

		Only leisure		All activities scaled		2013		2014		2015		Bicycle			PT
		Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test
Error components															
	σ_{alt1}	0.73	**14.98**	0.79	**27.92**	−0.87	**−11.21**	−0.77	**−9.05**	0.56	**4.99**			0.87	**1.76**
	σ_{alt2}	−0.55	**−9.17**	0.32	**6.56**	−0.54	**−5.09**	0.48	**4.18**	−0.66	**−6.82**	1.02	**11.04**		
	σ_{alt3}	0.76	**13.14**	0.77	**23.84**	0.76	**7.61**	0.67	**6.08**	0.76	**7.35**	−0.75	**−4.88**	−2.18	**−3.46**
	σ_{alt4}	1.55	**21.34**	0.59	**15.92**	−1.46	**−11.67**	−1.55	**−11.70**	−1.71	**−13.09**	−1.96	**−9.53**	−3.86	**−4.19**
Scale parameters				*Value*	*t-test0*	*t-test 1*									
	ϕ_{k2} Zero leisure short			1.10	**42.67**	**3.88**									
	ϕ_{k2} Zero leisure long			1.12	**43.04**	**4.61**									
Fit measures															
	Sample size	13889		29545		4797		4623		4469		4104			405
	Final log likelihood	−15163		−35607		−5250		−5053		−4161		−486			−486
	Robust Rho-square	0.32		0.20		0.32		0.32		0.37		0.26			0.26

Significant parameters are highlighted in bold.

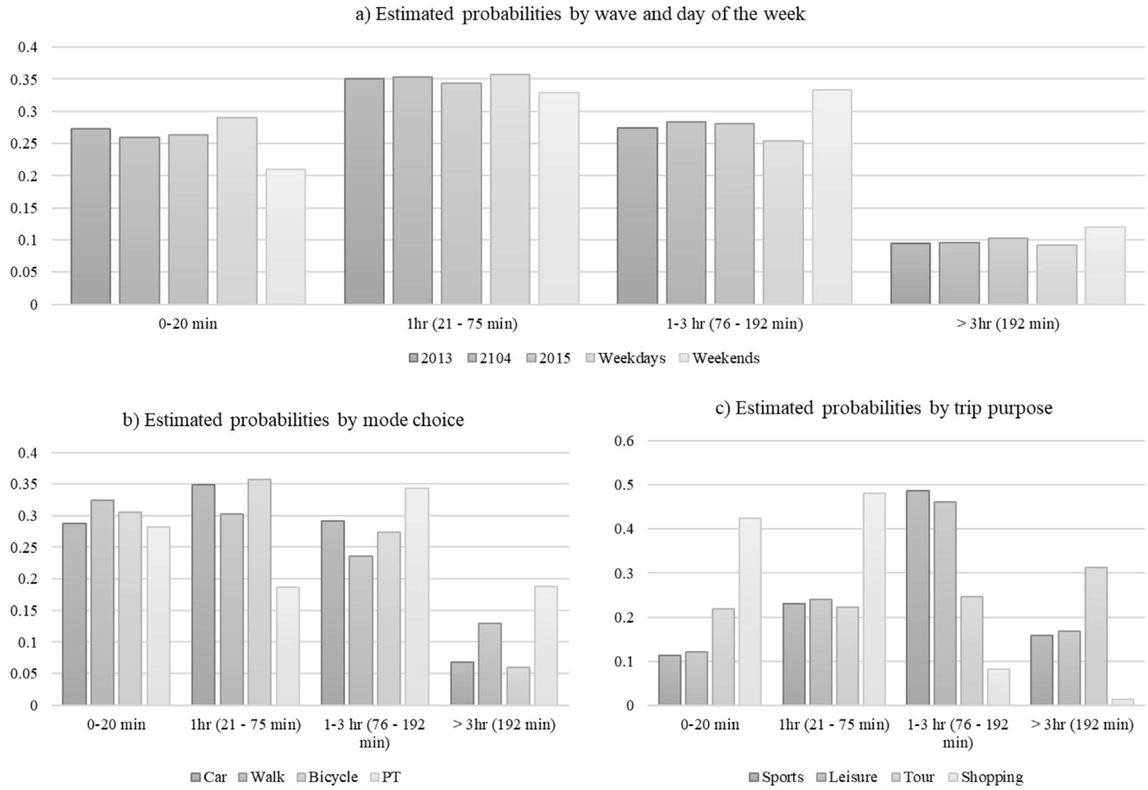

Fig. 2. Probabilities from the base model (leisure only).

duration (e.g., a day out program or evening party), morning (both early and late), early afternoon and evening are the preferred departure times, which supports what others have found (Bhat and Gossen, 2004). Usually, people do not go out in the evening for short-duration leisure activities.

Furthermore, the duration of activities that start in the late afternoon is more likely to be short. And, night time is a more likely departure time for short duration of outdoor leisure activities. Similarly, (Dane et al., 2014) found that leisure activities in the morning are more likely to be short.

Surprisingly, perceived accessibility of the surrounding area (e.g. parking, PT availability) does not affect the duration of outdoor leisure activities. However, using a car and public transport 4 days per week was found to be significant; frequent car users are unlikely to perform long-duration leisure activities and public transport users are also more likely to conduct short ones. The reason may be that regular driving or travelling affects their leisure pursuits; they may prefer indoor leisure activities and like to relax. The coefficient of preferred mode for going out can also be inferred; for instance, people prefer the use of public transport for long-duration leisure activities.

5.1.3. *Other variables*

The models for weekends and weekdays show that individuals are unlikely to perform a short-duration leisure activity when they frequently use the internet for social networking and entertainment. As expected, we found that short-duration outdoor leisure activities are highly likely to be conducted on workdays.

Important life events, such as the birth of a child in a household or the death of someone, getting a new job, change work address and schedule, moving in with someone, etc. were tested for the short-duration alternatives. All completely irrelevant parameters were then removed from the model specification. Respondents who reported life events also experienced a change in long-duration leisure activities. Complementing the work by Sharmeen et al. (2014), our results show that the duration of outdoor leisure activities is reduced under certain conditions (e.g., getting a new job), regardless of whether the need for the activities changes or not. Variety-seeking is positively associated with the longest activity durations (more than 3 h, alternative 4). It is interesting to note that 'variety-seeking' is statistically significant for all model specifications, which means that it is an important component of travel behaviour.

There have been many studies on the use of the ICTs on travel behaviour patterns, focusing on the question if ICTs are generating or substituting travel. The answer from the literature is still fairly unclear is becoming increasingly difficult to answer with the use of ICTs becoming integrated in our daily lifes (Lyons, 2014; Aguiléra et al., 2012). The variables related to ICT use were not statistically significant in these models at the 95% confidence level, and therefore removed from the final model especification.

5.2. Scaled model for zero-leisure days

The scaled model was estimated for all kinds of activities (leisure and non-leisure). Therefore, two groups were defined: with-leisure and zero-leisure days. As can be seen from the results, the scale parameter θ was found to be significantly different from 1 (t-stat 6.23). It indicates a significant difference in the variance between the reported 'with-leisure' and 'zero-leisure' days, since the group scale factor is normalised for the (with) leisure database. The estimated scaled (ϕ_k) parameters (long and short duration) are greater than 1, which indicates that the variance of the error term of the zero-leisure data is smaller than that of the leisure database. Also, both t-tests against 1 are statistically significant at the 95% confidence level. The coefficients are very similar in magnitude, which indicates similarities between the utilities of long and short duration activities when scaled by zero-leisure days. At the same time, the scaled factor represents the intrapersonal variation, since it accounts for the activities undertaken during the day at individual level.

The scale parameters indicate that the general utility of leisure duration is about 10% larger for those respondents who reported at least one day of zero leisure. The estimated parameters of the scaled model keep the same sign as in the base model, with the exception of a few variables. It means that considering a sample containing all activities yields different results given the correlation across the subgroups of the population. The panel effects also differ in sign, which means that taste heterogeneity is different between these two (leisure and non-leisure) samples. However, in the base model, the ASC values also show that short-duration activities are more likely to be performed than long-duration ones, which is consistent with the results of the scaled model.

When scaling the model, certain variables became statistically insignificant, and therefore were removed, such as income, being part of a couple, using the bicycle as transport to the activity, and the life event 'moving in together'. These socioeconomic characteristics and life events are only relevant for the explanation of leisure and recreational activities, but cannot explain all types of activities. Couples (without children) were found less willing to spend time on (all types of) short-duration activities. It means that they are more sensitive to long-duration activities, as also indicated by Bhat and Gossen (2004). Similarly, having no income is negatively associated with short-duration activities. This can be due to dependency on others (e.g., time spent with family members) and unemployment which may imply a high availability of free time.

5.2.1. Comparing dynamics of leisure activities and mode choice

The base model ('with-leisure' days only) is estimated for each wave, activity and transport mode of the activity; see Table 3. As can be seen, car, PT and bicycle are more likely to be used as mode of transport for short-duration activities than walking. On the other hand, for long-duration activities, walking is preferred, followed by bike and PT. For every purpose, the car is an important mode of transport, and when it comes to schedule and purpose, late afternoons are preferred for long-duration tours.

Table 3 also shows that frequency of internet use is only significant in the specification per day of the week (weekdays and weekend). For example, people who mainly use the internet for entertainment are less likely to perform short-duration leisure activities. Regarding life events, getting a job does influence the travel dynamics for outdoor leisure activities. However, this life event is more significant for weekend activities than for weekday activities, and less significant when using mode choice subgroups. Our results are partly consistent with Chatterjee et al. (2013), who found that life events influence the activities but contrast the findings related to transport modes by indicating that life events are not strong determinants for leisure activity durations when choosing certain modes (e.g. cycling). Similarly, key events over the life course seem to be only loosely associated with travel mode specific trip rates (Scheiner, 2014). But, the models per wave show that substantial differences can be obtained when the sample is divided into waves, in terms of the level of significance of the estimated parameters. This highlights the importance of longitudinal databases that allow modelling dynamics of travel behaviour.

5.2.2. Forecasting and implementation

Fig. 2 presents the probabilities of duration choices estimated by using the base model developed for leisure activities.[4]

As expected, the probability of performing short-duration outdoor leisure activities is higher during weekdays, whereas long-duration activities are more probable to occur during weekends. For sports, tours and other leisure activities, the probability of this being of a short duration dominates, whereas shopping activity is more likely to be undertaken for short durations. For the transport mode choice, walking and cycling have the lowest probability to be used for short-duration activities. This can be associated with the findings on travel time. Public transport is more attractive for long duration activities.

6. Conclusions

Understanding the dynamics of leisure activity duration is a very complex task; the diversity and flexibility of such activities are a challenge for modelling travel behaviour. In this study, a set of mixed logit scaled models was developed to explore the travel behaviour and dynamics of outdoor leisure and recreational activities. This paper provides an empirical analysis and discusses the dynamics and intrapersonal variation of duration of leisure activities; the analysis is based on discrete choice models, using data from the largest ongoing mobility panel in the world. These estimations can be used to forecast more accurate transport models, based on more realistic travel costs. We estimated an error component for the mixed logit model to account for heterogeneity effects between individuals and scaled utilities of zero leisure-days. We specifically addressed the issue of different activity purposes and week/end days to

[4] Separate models were estimated for each transport mode (walk, PT, bike and car) and activity type. Forecasting is based on the corresponding set of parameters per mode or activity type. Model estimations are available upon request.

analyse the dynamics of leisure activities over time. The model also accounts for the effects of life events as well as travel-related, socio-demographic and other variables.

The results firstly show that socioeconomic characteristics (gender, income, car ownership) and travel-related factors are important estimators of leisure activity duration. Specifically, travel time and departure time were found dominant over socioeconomic or other variables, whereas life events have a minimal effect on the duration of leisure activities. Furthermore, the results show the importance of analysing dynamics in very specific contexts, such as day of the week (weekdays versus weekend days), activity purposes and transport mode choice. They also underline the importance of measuring weekly-based mobility (Cherchi et al., 2017), specified by mode choice and days of the week. Secondly, our paper shows the potential of panel data to cover intrapersonal variations and individual heterogeneity. We find significant intrapersonal correlation in leisure activities. Using panel data thus adds a temporal (dynamic) dimension. This finding should lead to better estimations of intrapersonal variation via scaled models in the future, as it demonstrates that duration and (weekly) frequency of activities are linked. Thirdly, and finally, the results points out the strong link between temporal (week, year) and spatial (activity type location) dimensions with transport mode choice, indicating those as important elements in travel costs for leisure activities.

In future research, this model of activity duration can be, firstly, extended to a multiple discrete continuous structure[5] when an individual faces multiple (discrete-continuous) choices (e.g. types of destinations, such as shopping places, or social places, etc.); and under specific temporal constraints (e.g. weekends and weekdays) of consumption. Such predictions can be the basis for more accurate transport models, considering corner solutions in which one or more alternatives is not consumed (Bhat, 2008), beyond the traditional analysis of commuters and peak time activities. Secondly, the state depence of activity durations with life events, changes of neighbourhood accessibility and mode preferences can be explored, given the availability of four waves of MPN data. Thirdly, probabilities relating to weekdays, transport mode and trip purpose can be applied in transport planning and land use measures, such as re-scheduling and connectivity of PT upon demand, enhancement of destination facilities (e.g., opening hours, parking facilities) or the monetary value of the welfare produced by engaging in leisure activities and visiting tourism attractions.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jocm.2018.03.003.

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[5] In certain cases, estimating a discrete choice model from a continuous variable constrains the representation of multiple satiation effects (diminishing marginal returns), which are explicitly represented in MDCEV, without splitting the sample. When a set of type of activities composes a choice set (independently and identically distributed, i.i.d property) a multiple discrete continuous model can be developed for activity type and duration.

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