Transportation (2012) 39:791–806
DOI 10.1007/s11116-012-9402-0

Incorporating planned activities and events in a dynamic multi-day activity agenda generator

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Published online: 17 April 2012

Abstract Daily agenda formation is influenced by formal commitments, satisfaction of needs surpassing some threshold and the desire to conduct particular activities in anticipation of socially and religiously driven events such as birthdays, Christmas, etc. As part of a research program to develop a dynamic activity-based model of transport demand, this paper proposes a model to represent dynamic agenda formation, including these different underlying processes. Bayesian estimation of the model is based on data collected through a Web-based survey for a sample of approximately 300 respondents. The survey uses an extension of a 1-day activity diary where respondents are asked to recall activities in retrospect and to identify planned activities in prospect. Estimation results suggest that planned activities influence agenda formation in general, but that their significance and size depends on activity type, socio-demographics and dwelling characteristics.

Keywords Planned activities · Events · Retrospective questionnaire · Prospective survey · Activity-based modeling · Dynamic activity generation

Introduction

Over the last decade, progress in the development and application of activity-based transport demand models has been impressive. Models like CEMDAP (Bhat et al. 2004), Albatross (Arentze and Timmermans 2004), Famos (Pendyala et al. 2005) and TASHA

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(Roorda et al. 2008) are fully operational and provide planning support for policy makers. Nevertheless, existing activity-based models still have their limitations. Perhaps the most obvious of these is the lack of dynamics. Consequently, high on the research agenda is the development of dynamic activity-based models of transport demand. Over the last few years some progress has been made. Examples include activity scheduling for a multi-day period (Habib and Miller 2008; Auld et al. 2011a) and the dynamic generation of activities based on the needs they satisfy or induce (Miller 2004; Arentze and Timmermans 2009a; Märki et al. 2011).

Another new topic that might improve the performance of the current activity-based approaches concerns incorporating socially and culturally driven events into the activity generation part of activity-based models (Arentze and Timmermans 2009b). The notion that individuals are part of a social system implies that individuals participate in social and cultural events that occur on a regular or irregular basis, but which will disrupt their habitual daily activity patterns. Examples of events are celebrating birthdays, anniversaries, Christmas, New Year's Eve, sports tournaments, going on holiday, etc. In addition, planned future activities will affect the activity scheduling process of individuals. For example, if an individual has planned to go to a birthday party the next day, the person may not participate in a social activity on the current day (the scarce time can better be spent in another way).

Several surveys reported that many of the executed activities are planned ahead. For example, Chen and Kitamura (2000) found that 30–45 % of the performed activities were scheduled a day before or earlier and that the majority of planned activities were conducted. Similar results were found by Doherty (2005). He investigated the process of timing of scheduling decisions, as individuals frequently plan and re-plan their activities at various stages in time, and often without being conscious about it. Doherty found that more than 30 % of all activities are impulsive, almost 20 % are planned on the same day, approximately 25 % are planned earlier, and the remainder is either planned years before or routine. Furthermore, Auld et al. (2011b) used a prompted recall activity–travel survey (using GPS data loggers) as well as a single day activity planning diary in order to investigate the activity planning process. They found that most of the activities and activity attributes are routine (approximately 30 %), especially the location of the activity (46 %), and more than 20 % of the activities was pre-planned.

An important finding of a stated adaptation experiment carried out by Nijland et al. (2009a) is that planned activities seem to be less flexible for modification in case of delay. Pre-planned activities are less frequently skipped or postponed when there is less time available to conduct the activity. Comparable results were reported by Roorda and Andre (2007). An explanation can be that in most cases, planned activities are performed together with others and are, therefore, more difficult to change. Given the high number and the inflexibility of pre-planned activities, we argue that the scheduling effects of planned activities and events should be included in the next generation of dynamic activity-based models.

With the aim of integrating the different dynamics of the activity generation process into one new framework, Arentze and Timmermans (2009a) and Arentze et al. (2010) formulated a need-based model. They defined the utility of an activity in terms of its contribution to the satisfaction of dynamically changing needs at the person and household level. This dynamic activity generator predicts activity agendas for multiple consecutive days and allows for interaction effects among activities. In an attempt to bring the event-based theory and the need-based approach together, Nijland et al. (2009b) extended the need-based model by adding the possible effects of planned activities and events.

The purpose of the present paper is to address the question of how rhythms in need-driving activities are merged with pre-planned activities and events. In order to estimate the parameters of the extended need-based model, a web-based survey was administered among a sample of roughly 300 respondents. The survey included socioeconomic and demographic variables, available time for discretionary activities (i.e., the amount of time spent on work or education on a day), and for a list of 37 social, leisure, and sports activities: activity history (e.g., time elapsed since last performance) and activity planning variables (is the activity already planned and when).

This paper is structured as follows. First, the RUM specification of the need-based concepts and model will be briefly summarized. This is followed by a description of the design of the survey, the characteristics of the sample, and the data preparation method. Subsequently, the results of the parameter estimations and the effects of pre-planned activities and events will be reported. Finally, the last section discusses the main conclusions and implications of the results of the estimations, and identifies remaining issues for future research.

Need-based theory and model

In this section the basic equations of a model for predicting the timing of activities in a multi-day time frame that is proposed in Arentze et al. (2010) will be briefly outlined. This is followed by an addition to the model specification that takes into account multi-day interaction effects among activities (as shown in Nijland et al. 2011). This section ends with an extension to the estimation procedure that considers the effects of planned activities and future events.

Basic equations

The model is based on concepts from a more theoretical need-based model of activity generation, which we cited above, and has parameters that should be identifiable based on observed temporal patterns of activities. The model predicts a multi-day activity pattern agenda for a given person for a period of arbitrary length. Rather than solving some resource allocation optimization problem, the model assumes that individuals make activity–selection decisions on a daily basis.

While the need-based model allows for interactions among activities and among household members, the RUM model used for first estimation considers a more limited situation, where an individual is faced with a decision to conduct an activity a on a current day d given that the last time the activity was undertaken was on day $s < d$ (i.e., the time elapsed equals $d - s$ days). The utility of conducting an activity of type a on a given day d is defined as:

$$U_a(s,d) = V_{1a,d-s} + V_{2,ad} + \varepsilon_{1as} + \varepsilon_{2ad} \quad (1)$$

where d is the current day, s is the day activity a was carried out the last time before d, $V_{1a,d-s}$ is the utility of satisfying the need for activity a built-up between s and d, $V_{2,ad}$ is a (positive or negative) preference for conducting activity a on day d, and the error terms ε_{1as} and ε_{2ad} are associated with need build-up and day preferences, respectively.

The first term implies that a need for an activity grows with the time elapsed since day s. In order to reduce the number of parameters, the RUM model assumed a simple linear function:

$$V_{1at} = \beta_a t \tag{2}$$

where β_a is a growth rate and t is the length of the need growth period between s and d ($t = d - s$). The day-component is parameterized in a straightforward way as:

$$V_{2ad} = \alpha_{ad} \tag{3}$$

where α_{ad} is a preference for conducting activity a on day d.

At present, the model leaves activity duration out of consideration and defines the threshold on the level of the utility of the activity. Thus, the decision rule in the present model is formulated as 'conduct the activity at the earliest moment when the following condition holds':

$$U_a(s, d) > u_d^o \tag{4}$$

where u_d^o represents a threshold for implementing activities on day d, given existing time demands on that day. Defined in this manner, the need-growth parameter β for some activity will capture the time needed to overcome the threshold taking into consideration an average or normal duration of that activity.

The choice model is derived from the assumption that ε_1, is Gumbel distributed, whereas the second error term, ε_2, is normally distributed ($\varepsilon_2 \sim N(0, \sigma)$) and simulated. Given this assumption, an ordered-logit framework can be derived from decision rule (3) (Arentze et al. 2010), having the following form:

$$P_a(d|s) = \frac{\exp[Z_a(s,d)]}{1 + \exp[Z_a(s,d)]} - \frac{\exp[\max_{k=s+1}^{d-1}[Z_{ak}(s,k)]]}{1 + \exp[\max_{k=s+1}^{d-1}[Z_a(s,k)]]} \tag{5}$$

where

$$Z_a(s,d) \equiv V_{1a,d-s} + V_{2ad} + \varepsilon_{2ad} - u_d^o \tag{6}$$

Note that the conditional probabilities sum up to one across days after s:

$$\sum_{d>s} P_a(d|s) = 1 \tag{7}$$

As implied by this equation, P defines a choice probability distribution across days after s. In other words, the model predicts for a given activity and individual the probability that the activity will be conducted on future day d, given the information that it was conducted the last time on an earlier day s. Hereby the model takes into account possible day-varying conditions related to day preferences and time budgets for each day from s to d as well as the simultaneous process of need build-up from day to day. Note that the model determines whether or not an activity of a given type is conducted on a certain day; it leaves out of consideration whether this involves a single or multiple episodes of the activity on the same day. In the model, a change in preference or time-budget for a certain day of the week does not only have an impact on the probability of conducting the activity on the day concerned. As a secondary effect, also the probabilities for other days will undergo a change. Secondary effects emerge because a need for the activity needs time to rebuild after the activity has been carried out.

Interactions among activities

This section presents a method to define the need-based framework in such a way that it allows for interactions among activities, as proposed in earlier work (Nijland et al. 2011). As for needs, interactions occur if one activity increases or reduces the need of another activity. For example, a shopping activity can partially satisfy a need for a social activity, a need for being out in the open air, and a need for a leisure activity (Nijland et al. 2010). We use the following way to incorporate this notion in the function for the need-related utility component:

$$V_{1a}(s,d) = \sum_{t=s+1}^{d} \left(\beta_a + \sum_j \delta_{aj} I_{tj} \right) - \sum_j \delta_{ja} \tag{8}$$

where β_a is the size of daily increase of a need for activity a, as before, and δ_{aj} is an increase in need of activity a caused by some other activity j, $I_{tj} = 1$ if activity j is conducted on day t and $I_{tj} = 0$, otherwise. In this equation, the parameters, δ_{aj} and δ_{ja} capture both sides of the interactions: the first parameter makes sure that the utility of a increases when other activities conducted before day d have an increasing impact on the need for a and the second parameter makes sure that the utility of a decreases when a has an increasing impact on needs related to other activities. Thus, the first term on the RHS of Eq. (8) represents the total need on a day d for the activity, depending on the history. Given the assumption that the existing need of an activity is fully satisfied when the activity is conducted, the total need for the activity is equal to a utility. The last term represents the total increase of needs for other activities caused by the activity. The need increase for other activities must be discounted, as it is a disutility.

The parameters β_a, α_{ad}, u^0 and δ_{aj}, are estimated based on observations of activity timing choices. The expected signs for the β (need growth) and u (threshold) parameters are positive. As for the δ parameters (need-based interactions), a positive as well as a negative sign is a possible outcome of the estimation. A value of $\delta_{aj} > 0$ would represent a negative substitution effect (activity j increases the need for a) and $\delta_{aj} < 0$ a positive substitution effect (activity j decreases the need for a). It is possible that the substitution effects are a-symmetric in the sense that $\delta_{aj} \neq \delta_{ja}$. Although we do expect that the two parameters have the same sign, we do not restrict the search range for the parameter in a loglikelihood estimation. For need growth (β) and threshold (μ) we expect that an influence of socio-demographic variables is particularly significant. Therefore, for these parameters the following decomposition of parameters will be used:

$$\beta_a = \beta_a^0 + \sum_k \beta_{ak} X_{1ak} \tag{9}$$

$$u_d^{\mathrm{o}} = \mu_d^0 + \sum_m \mu_m X_{2dm} \tag{10}$$

where X_1, X_2 are sets of explanatory variables of activity needs (Eq. 9) and time budgets (Eq. 10), β^0 and μ^0 are base parameters and β and μ are parameters representing effects on these baseline parameters. For α and δ parameters we do not estimate such effect parameters for reasons of parsimony (considering the degrees of freedom of the model). Finally, we use a mixed logit framework to estimate the scale σ_a of the day-based error term ε_{2i} ($\varepsilon_{2i} \sim N(0, \sigma_a)$) for each activity a. Thus, the framework takes into account that variance in utility can differ between activities due to unobserved daily circumstances.

Planned activities and events

In this section we propose a method to estimate possible effects of planned activities and events on the decision to schedule an activity on a particular day, by using the prospective data collected in the survey described below. In theory, there are different ways in which an anticipated future activity can influence a decision to implement a given current activity. The theoretical model introduced in Nijland et al. (2009b) showed a mechanism through which future activities can lead to postponement or cancelling of a current activity. According to this mechanism, an activity might be postponed until the day some other activity is planned to save time (e.g., conduct both activities on a same trip) or even cancelled if the planned activity can satisfy completely or partly a same set of needs. It is conceivable that inverse effects may also occur, i.e., that a future planned activity leads to conducting an activity earlier, for example, due to time availability (e.g., there will not be time tomorrow) or preparation for a future activity (e.g., need to do grocery shopping for a social visit tomorrow). To allow for positive and negative sign, we estimate the effects as an effect on the threshold parameter, i.e., an increase or decrease of the threshold to conduct the activity.

Thus, the model proposed here assumes that planned future activities possibly will affect the threshold. Therefore, a new component will be added to Eq. (10) that explains the effects of each planned activity j on the utility of conducting activity a on day d. As the influence of a planned activity or event close to day d will be considerably higher than the effect of an activity planned in the distant future, the inverse of the amount of days between day d and the planned activity (t_j) is incorporated in the equation in the following way:

$$u^{\mathrm{o}}_{daj} = \mu^0_d + \sum_m \mu_m X_{2dm} + \gamma_{aj}(1/t_j) \tag{11}$$

where γ_{aj} is the threshold effect of an activity a on planned activity j, which is to be estimated. Note that in this formulation the possible influence of a future activity rapidly decreases with the days the activity is ahead meaning that effects are particularly focused on a single day time difference (the future is the next day). Other functions with steeper or flatter slope were tried as well, but this function appeared to fit best the observations.

The data collected in the main survey provides us information on if and when the activities were already planned. As we impose no restrictions on the ranges for the gamma parameters, the formulation given by Eq. (11) also allows inverse effects and, hence, provides a suitable framework for exploring the relationships.

Model estimation

Equation (5) defines a probability distribution across days d after s. Formulated in that form, the probabilities cannot be directly used to define likelihoods of observations in the present case. In the survey conducted to estimate the model (see below) individuals recorded their activity agenda for a given day (d) and in addition for an exhaustive list of activities the day the activity was performed the last time (s). Thus, rather than a probability distribution across days, a binary probability of observing a particular activity on the survey day is needed. The required binary probabilities can be derived from the probabilities in the original form (Nijland et al. 2011). According to the model, the probability that the activity has not been conducted in the period from $s + 1$ and $d - 1$ is defined as:

$$Q_i(d|s) = 1 - \frac{\exp[\max_{k=s+1}^{d-1}[Z_i(s,k)]]}{1 + \exp[\max_{k=s+1}^{d-1}[Z_i(s,k)]]} \tag{12}$$

Therefore, the probability of observing i in the agenda for day d knowing that the activity has not been conducted until that day is given by:

$$L_i(1|d,s) = P_i(d|s)/Q_i(d|s) \tag{13}$$

$L_i(1|d,s)$ is the likelihood of observing activity i given observation day d and recalled last day s. This likelihood has the following property:

$$L_i(1|d,s) + L_i(0|d,s) = 1 \tag{14}$$

where $L_i(0|d,s)$ is the likelihood of not observing activity i given observation day d and recalled last day s. Using this latter binary form, a likelihood function for a sample of observations can be defined in a straight-forward way (see Nijland et al. 2011).

The likelihood function (or loglikelihood function) appears to be non-smooth in the area of the optimum values of β parameters in particular. Furthermore, due to the dependency relationship between activity probabilities across days, i.e., the secondary effects, convergence of search processes for optimal parameter values in standard loglikelihood methods is very slow. To circumvent these problems, Nijland et al. (2011) proposed a Bayesian method of estimating parameters. This method implements an incremental Bayesian learning process. Initially, an uniform distribution is assumed for each parameter of the model, reflecting a situation where no prior knowledge about parameter values exists. Observations are processed one at a time. Processing an observation means that for each parameter the posterior distribution is determined assuming expected values for all other parameters. The priors in each next observation are set to the posteriors obtained from the last observation. After all cases have been processed, the posterior distributions represent final estimates. Note that in this method each observation is used only once to update beliefs about the parameters. This is required because the same piece of information should not be used more than once in belief formation.

Data collection

A survey was carried out to collect the retrospective and prospective data that was needed to estimate the model explained above. In order to reduce respondent burden and shorten the data entry time, the developed questionnaire was administered through the internet. The complete questionnaire consisted of seven different parts. For estimating the parameters we focus on five of them.

Socio-economic and demographic variables

Person, household, and dwelling attributes are essential for the analyses of spatial behaviour of individuals. Questions concerning, for example, gender, age, household composition, income, dwelling type, education level, occupation, number of children, age youngest child, living area, car availability, and driver's license, were included in the survey.

Time budgets

In the so-called standard week pattern the respondents had to indicate, for every day of the week, which of the given activities they normally (phrased as 'almost always') conduct on that day. For each selected activity the subjects had to specify the usual duration and travel time. Eighteen activities were included in this part, like work, education, bring/collect child(ren), grocery shopping and some sports, leisure and social activities. The decision to use the latter ones was based on frequencies of those activities indicated by respondents in the Amadeus survey (Timmermans et al. 2002). If only a very small percentage of the 1,600 respondents conducted the activity at least once a week, the activity was not included in the standard week pattern. Roughly, the standard week pattern of a respondent represents the time pressure on the different days of the week. Particularly, the time spent on work or education plays an important role in the dynamic need-based model.

Activity pattern

The subjects were asked to indicate which activities they conducted the day before they filled out the questionnaire. For each of these activities, they were asked to provide details about activity duration, flexibility of the activity (could activity be conducted on another day instead of the day considered), planning time horizon, travel time, transport mode and accompanying persons. Furthermore, respondents were asked to give some information on the weather conditions of the day concerned.

History

In this part subjects had to indicate, for a list of leisure, sports, and service-related activities, when the last time was that they conducted the activities. They had two ways to indicate this. First, they could specify the date, which could be selected with the help of a calendar. Second, they could indicate how many days, weeks or months ago they last performed the activity. A third option was n/a (not applicable) which could be marked if it was longer than 6 months ago or if they never do the activity. The history information was requested for the exhaustive list of 37 activities (not just the activities conducted on the day before).

Future

This part of the questionnaire was similar to the history part. However in this case respondents had to indicate for the same list of 37 activities if and when the activities were already planned. Again, subjects could indicate the date. If they did not know the date yet, they could indicate in which term (the next few days, next week, the next few weeks, next month or later) they were planning to conduct the activity. Not applicable (n/a) could be marked if the subject did not plan the activity (yet).

Sample characteristics

In order to achieve a representative sample of respondents, several neighborhoods were selected in the city of Eindhoven and seven villages in the Eindhoven region. Attention was paid to the distribution over different neighborhoods in terms of the density, the distance to the city/town centre, rich and poor areas, etc. In June and July 2009, around 4,000 invitation cards were distributed to households in the selected neighborhoods. Additionally, by e-mail another 400 individuals, who in an earlier survey had indicated their willingness to participate again in a web-based survey, were approached. The day of the activity pattern had to be spread over the days of the week. In order to achieve this, the distribution of the invitation cards and e-mails was stretched over all days of the week. To encourage potential subjects to participate in the survey, twenty vouchers of 50 Euros were assigned to respondents through a lottery. In total, 438 individuals started and 290 of them finished the web-based questionnaire. The average completion time of the Internet survey was about 25 min, which is acceptable.

Concerning a few relevant socioeconomic variables, Table 1 compares the characteristics of the sample to the Dutch population. The table shows that the sample is reasonably representative, apart from an overrepresentation of above-average educated respondents. This bias is typical for (web-based) questionnaires in general (Bricka and Zmud 2003). Furthermore, the elderly (65+ years) and young persons (<25 years) are somewhat underrepresented, whereas households consisting of two persons (married or living together) are a little overrepresented.

Data preparation

In the current paper, the activity data used for the analyses consists of the cases where the subject indicated the date of (or the time passed since) the last performance of the activity. The variable 'time passed since last performance' represented the number of days between the last performance and the previous day (the day of the activity pattern). On the latter day, the activity could either be conducted or not be conducted. Both of these options were incorporated in the model estimation. In total, approximately 4,200 cases could be used for the analyses. By combining some of the most regularly undertaken activities; five activity groups were formed, namely: daily shopping, non-daily/fun shopping, social visits, leisure, and sports. Note that the activity groups are only used at the level of the parameter estimation, in the model the activities are applied individually (i.e., the time elapsed since last performance of the activity is calculated for the activities separately, not for the

Table 1 Sample characteristics

	Sample (%)	Population (%)
Gender		
Female	53	50.5
Male	47	49.5
Age (years)		
15–25	7	15
25–45	48	37
45–65	34	33
65–85	10	16
Education level		
Below average	14	35
Average	25	41
Above average	61	24
Household composition		
Single, no children	23	35
Single, children	3	6
Double, no children	38	29
Double, children	33	29
Multiple persons	1	1

activity group in general). The second part of Table 2 shows which activities were taken together. All in all those activities contain 2,621 cases which can be used for estimating the parameters of the need-based activity generation model and consequently the effects of planned activities and events.

The need-based model and the Bayesian estimation method to estimate the model (using the Bayesian estimation method described in Nijland et al. (2011)) were both developed in C. Based on the number of cases available for each (dummy) variable, we selected and categorized the explanatory variables on individual and household levels that were to be included in the analysis. This number may not be too low in order to get a reliable result. A threshold of 400 cases was used.

The person, household, and dwelling attributes shown in Table 2 were included as explanatory variables of activity needs (X_1, Eq. 9). We used work hours (as a continuous variable) and car availability (dummy coded) as explanatory variables (X_2, Eq. 10) for the threshold value, since those variables are likely to affect time budgets on a day. The β (need growth), α (day preferences) and day-error-scale parameters are estimated for each activity group separately. The number of draws was set as $K = 100$. In the current formulation of the model, temporal constraints such as limited opening hours are not represented separately from other, individual-related constraints. All constraints are represented by a single threshold function. It is possible to extend the model and represent the latter constraints as an all-or-nothing availability variable for days. We leave this for future research.

Results

Table 3 shows the results of the estimation of the model including the possible effects of planned activities and events. Several socioeconomic variables affect the base level of β. For example, men seem to have a shorter need-rebuild time for grocery shopping than women if future activities are taken into account. On the other hand, their need-rebuild duration is longer in case of leisure activities. When looking at the age groups, it can be seen that the youngest age group (30−) shows significant positive effects on needs for non-daily shopping and social visits. This means that if available time, specific day preferences, interactions among activities, planned activities, and other attributes are the same, this group would participate in social and non-daily shopping activities more often. In addition, apart from social visits and leisure activities, the eldest age group (60+) participates in grocery shopping more frequently. However, sports activities are less often conducted by older persons. When the individual is between 40 and 60 years old, the need-rebuild time for leisure activities seems to be longer. In terms of household composition, the results show that respondents living in a household with children have shorter need-rebuild times for non-daily shopping and sports, and longer need build-up times for leisure activities, whereas being single decreases the need-rebuild time for sports activities. In addition, families with young children (youngest child younger than 6 years old) also show a lower need growth rate for leisure. Furthermore, we find that individuals living in a house with garden have a shorter need-rebuild time for grocery shopping, compared to respondents living in a flat/apartment. However, subjects who live in an apartment seem to participate in sports activities more frequently. The income level also affects the interval time: when the household income is lower than average, the frequency of (grocery and non-daily) shopping increases, but on the other hand, leisure activities are conducted less often. Higher income households, on the contrary, engage less frequently in non-daily or fun

Table 2 Variables and activities included in the need-based model

Variable	Code	Description/range
Day of the week	mon	Monday
	tue	Tuesday
	wed	Wednesday
	thu	Thursday
	fri	Friday
	sat	Saturday
	sun	Sunday
Gender	male	Male
	female	Female
Age group	age30−	<30 years old
	age3040	30–39 years old
	age4050	40–49 years old
	age5060	50–59 years old
	age60+	60 years and older
Household composition	hh_s_no	Single, no children
	hh_sd_c	Single or double, with child(ren)
	hh_rst	Double, no children, living in at parents/ relatives, student or group accommodation
Household income	ibav	Below average
	i1av	Average
	iaav	Above average
Age youngest child	aych06	0–5 years old
	aych6+	6 years and older
Hours spent work a day	tswork	Continuous
Education level	edul	Low
	edu1av	
	eduh	High
Living area	city	City
	village	Village, countryside
Dwelling type	*dwap*	Flat, apartment
	dwgarden	House
Car availability	carA	Yes, always
	carO	Yes, to be agreed with others
	carN	No
Grocery shopping	G shopping	Grocery shopping
Non-daily shopping	ND shop	Non-daily shopping, fun shopping
Social visits	Social visits	Visiting relatives/friends, receiving visitors
Leisure	Leisure	Going out for dinner, visiting a theatre, concert, museum, café, bar or discotheque, going to the cinema, a day out (visit a city, recreation park)
Sports	Sports	Sports outdoors, sports indoors

Base levels are shown in italics

Table 3 Estimation need-based model including planned activities and events

	Grocery shopping Estimate	Non-daily shopping Estimate	Social visits Estimate	Leisure Estimate	Sports Estimate
Variable					
β 0	*0.767*	*0.309*	*0.445*	*0.251*	*0.073*
β male	*0.115*	−0.122	−0.102	*−0.181*	−0.093
β age30−	−0.019	*0.127*	*0.143*	−0.078	−0.016
β age4050	−0.084	−0.067	*−0.171*	*−0.127*	−0.078
β age5060	−0.043	−0.047	0.076	*−0.104*	−0.054
β age60+	*0.197*	−0.052	*0.16*	*0.133*	*−0.063*
β hh_sd_c	0.020	*0.036*	0.049	*−0.151*	*0.167*
β hh_s_no	−0.132	−0.109	0.077	−0.062	*−0.165*
β dwgarden	*0.102*	0.001	−0.071	−0.021	*−0.178*
β ibav	*0.169*	*0.162*	0.053	*−0.137*	0.125
β iaav	−0.016	*−0.159*	−0.093	−0.023	0.095
β edul	−0.064	−0.062	0.051	−0.120	−0.057
β eduh	0.064	0.008	*−0.054*	−0.096	*−0.163*
β aych06	0.163	−0.039	0.020	*−0.136*	0.046
β city	*0.110*	*−0.065*	−0.060	*−0.141*	−0.014
α mon	0.250	*−0.646*	−0.171	*0.536*	*−0.519*
α tue	−0.226	−0.386	−0.129	*−0.531*	*0.302*
α thu	*−0.311*	*−0.618*	−0.155	0.022	*0.378*
α fri	−0.187	*0.354*	0.152	−0.177	0.229
α sat	0.243	−0.154	0.339	*0.383*	*−0.279*
α sun	−0.524	*−0.401*	0.225	−0.441	0.186
DaySTDEV	*2.095*	*2.47*	*3.760*	*2.055*	*3.501*
δ G Shopping	0.319	*0.811*	0.219	0.067	0.224
δ ND shop	−0.018	*0.461*	*0.403*	*−0.424*	−0.105
δ Social visits	0.253	0.353	0.126	*0.270*	*−0.538*
δ Leisure	0.049	−0.045	0.252	0.255	0.110
δ Sports	0.199	−0.070	0.055	−0.138	0.277
γ G Shopping	−0.125	0.095	0.358	−0.029	0.183
γ ND shop	0.444	−0.016	0.375	0.233	0.205
γ Social visits	*−0.598*	−0.374	−0.076	0.119	−0.255
γ Leisure	−0.191	*−0.305*	0.004	−0.311	0.192
γ Sports	−0.348	*0.648*	0.092	*−0.325*	−0.208
All activities					
Thr0	*1.172*			LL	−709.842
ThrTswork	*0.154*			LL0	−1604.77
ThrcarA	0.122			ρ^2	0.558
ThrcarO	−0.051	Nr. of obs.	2,621	ρ^2 (adj.)	0.455

The significant estimates are shown in italics

shopping activities. The results of the different education levels show that higher educated respondents have longer need build-up times for needs for visiting relatives/friends and sports activities. Finally, individuals living in a city show longer interval times in case of non-daily shopping and leisure activities. However, city-dwellers have shorter build-up times for needs for daily shopping. This result seems behaviourally intuitive as there are more grocery stores in cities, which indicates that persons live closer to a store and, therefore, may have developed higher-frequency solutions for re-stocking. In sum, the results on this level indicate that need build-up rates for specific activities co-vary with socio-demographic variables as well as characteristics of the dwelling. This indicates that different patterns in activity generation are formed across individuals depending on the life-cycle and situational conditions in which they reside.

When looking at the day preferences, some significant parameters are also apparent. For Mondays, negative signs are found in case of non-daily shopping and sports activities, but leisure activities show a positive preference for Monday. On Tuesdays persons seem to prefer sports activities, whereas leisure activities are not preferred on that day. Thursdays seem to be less popular to go (grocery and non-daily) shopping, while sports activities are preferably conducted on a Thursday. There is a preference for non-daily shopping on Fridays. On Saturdays, individuals do not prefer to participate in sports activities, however they prefer to perform leisure activities on this day. Finally, a negative preference exists for conducting non-daily shopping activities on Sundays. This can be caused by the fact that stores for non-daily shopping are not open every Sunday in the Eindhoven region (usually only one Sunday a month). In sum, the results on this level reveal that pronounced preferences exist for day of the week, especially regarding activities such as shopping and leisure that depend on availability of specific (urban) facilities.

The δ estimates show some significant parameters as well. They indicate whether activities within the row activity group influence the need for an activity from the column activity group. The results show that both grocery and non-daily shopping increase the need for non-daily shopping. Furthermore, non-daily or fun shopping also raises the need for a Social visit. Conversely, the shopping activity decreases the need for leisure activities (or people who often conduct non-daily shopping activities tend to undertake leisure activities less frequently than others). An explanation for this might be that non-daily or fun shopping (partly) satisfies similar needs as leisure activities (Nijland et al. 2010) (e.g., social contact, physical exercise, entertainment). Social visits increase the need for Leisure activities, but decrease the need for Sports (or people who often engage in social activities (i.e., visiting relatives or friends) tend to participate in sport activities less frequently than others). This might be caused by the fact that sports activities done together with others also satisfy the need for social contact.

The most interesting results of the estimation shown in Table 3 are the effects of planned activities (γ). Most of the significant effects on the threshold have a negative sign. This means that the planned activities lower the threshold. As noted before, there are at least two interpretations possible for a decrease of the threshold: (1) need induction: a planned social activity might trigger grocery shopping as a preparation for the activity (Arentze and Timmermans 2009b), and (2) time use planning; e.g., if a social activity is planned for the next day, then there is not much time left on that day for maintenance activities such as grocery shopping, so it would be better to execute the latter activities today. The threshold lowering effects are found in the case of grocery shopping, when a social contact activity is planned, for non-daily shopping in anticipation of a leisure activity, and in the case of leisure activities, when a sports activity is part of the activity agenda of a day in the near future. The only significant threshold increasing effect is displayed by a planned sports activity on non-daily or fun shopping. A planned sports activity increases the threshold for conducting non-daily shopping. This hints at a possibility that a sports activity partly satisfies a same need as non-daily shopping such that when a sports activity is planned (e.g., the next day) a non-daily shopping activity is skipped.

The threshold effects show that the amount of time spent on paid work on a day increases the threshold value and, as a consequence, decreases the probability of participating in other out-of-home activities on that day, which seems to be logical. Car availability does not have a significant impact on the threshold value in this study. The ρ^2 of the estimation was determined by using the log-likelihood of the estimated model and the log-likelihood of a null-model. Note that a complete null model, where all parameters are set to zero is not a good indicator of the reference goodness-of-fit in that the need-growth and threshold value cannot be equal to zero. In order to find an appropriate reference goodness-of-fit, ‘mean’ values of the estimated intercepts of β and a value close to the estimated threshold intercept parameter were used to calculate the Log-likelihood of a null-model. For the threshold intercept we chose a value of 2 and for all intercept β parameters 0.5 was chosen. All other parameters were set to zero. The ρ^2 calculated in that way is 0.558, which indicates a good performance of the model. However, the adjusted ρ^2 with a value of 0.455 is obviously lower. This reflects the relatively large number of parameters of the model compared to the number of observations, but still indicates that goodness-of-fit is acceptable. It should be noted, that one of the estimates has an extremely high t value (DaySTDEV in case of leisure). This means that the parameter is significant, however, the variable is not distributed normally.

Conclusions

The research project described in this paper aimed at investigating possible effects of planned activities and events on the activity scheduling process. It is assumed that the conduct of activities (partly) satisfies a set of underlying needs. Under stationary conditions, this would imply that the dynamics of agenda formation follow a wave-type rhythm only disturbed by daily variation of conditions that have an influence on time budget and preferences. However, inherently irregular and infrequent events such as birthday, vacations and Christmas trigger the need to become involved in related activities.

A model incorporating the effects of planned activities into a dynamic need-based model of activity generation has been formulated. Bayesian estimation methods were used to estimate a random utility specification of the formulated model. The significant results of the influences of planned activities indicate that there are several ways to explain the effects. While the positive estimates represent substitution effects (the planned activity or event satisfies similar needs), the negative estimates can be clarified by, for example, anticipation of time pressure on a near future day and preparation of a planned activity.

The influence of planning processes on activity generation has received scant attention in the activity-based literature. In this study, we showed how planned activities can be accommodated in a dynamic model of activity generation. The planning process itself is not considered by the model. Rather the model describes daily decisions of activity participation taking into account activities that have already been planned to take place on the same day or in the near future. Data needs of the model are modest. We showed that a relatively small extension of the existing one-day activity diary suffices to collect the data needed for estimation. The extension involves a prospective and a retrospective part. The retrospective part asks the respondent to recall for each activity of an exhaustive list to recall the day when the activity has been conducted the last time. On the other hand, the prospective part asks the respondent to indicate for the same list of activities whether and, if so, when a next episode of the activity is planned. Longitudinal data collections are costly. The model that we introduced in this study requires a relatively small extension of the existing activity diary and brings within reach a dynamic (history and future dependent) handling of activity generation processes. Future research should focus on the development of a model for longer-term planning of activities which, in addition, is needed to model activity-agenda formation processes.

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