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#### Abstract

The theory of the S-shaped utility functions that was developed by Joh et al. (2003) within the framework of their activity-based transport demand model Aurora, will be used in the present research as the underlying framework of a dynamic activity-based rescheduling approach. The aim of this paper is to examine the impact of different activity characteristics and situational attributes, namely activity duration, history, discretionary time, time of day, location and accompanying persons, on an individual's rescheduling decisions. In order to study the effect of these variables, different stated preference scenarios were included in a dynamic Internet-based survey that was provisionally tested on a small-scale pilot sample. The data gathered by the survey were used to estimate the fraction-utilities of the various attributes by means of a binary logit model.


## Keywords

S-shaped utility function, stated-preference, parameter estimation

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## 1. Introduction

The development of the activity-based approach in transportation research has provided a unifying framework for transport modelling. The rationale behind activity-based models is that travel demand is derived from activities people need or want to perform. The activity-based approach has various advantages compared to the classical trip and tour based models, but the ability to capture individual travel behaviour more realistically is one of the main reasons activity-based models are gradually being deployed to evaluate policy measures.

In order to obtain a useful evaluation of transport demand management measures, a thorough understanding of the way individuals compose their activity schedule and rescheduling their activities is essential. To that effect, Timmermans et al. (2001), Joh et al. (2002, 2003, 2004) developed the Aurora model, a dynamic activity-based model that explains and predicts how individuals change their activity schedule during the day as a result of e.g. unexpected events or time pressure. Unlike other researchers, who used a logarithmic utility function, Aurora is based on S-shaped utility functions. Nijland et al. (2006) provide some empirical support for the relevance of S-shaped utility functions. In the context of developing the FEATHERS model (Janssens et al., 2006), this study is partly replicated and extended, and the first results of this effort are reported in this paper. The S-shaped utility function that is considered in this paper is based on the notion that the utility of an activity is not exclusively dependent on the duration of that activity, as is the case in most other utility-based approaches. Because the decisions that constitute the rescheduling process are too complex to take only one explanatory variable into account, other relevant aspects are incorporated in the S-shaped utility function as well, such as time of day, discretionary time available during the day and the location where the activity is conducted. The time elapsed since an activity has last been performed is another aspect that influences the value of the utility and is therefore incorporated in the S-shaped utility function. Some activities will be jointly performed with other people, either household members or not. The influence of these companions on the utility is the last aspect that will be examined in this paper.

In order to assess the influence of these various aspects on the utility, the effect of the corresponding variables on the parameters of the S-shaped utility function has to be determined. The utility function was fitted on data from an extensive survey. This survey consisted of three parts: a questionnaire to collect socio-demographic information, some questions about frequently visited locations for a specific activity and a stated-preference
experiment that provided each respondent with a number of hypothetical scenarios. The scenarios differed in the values of the investigated activity attributes that were presented to the respondents.

As the utility of an activity is an abstract concept, it cannot be observed directly. To overcome this problem, respondents were asked - for each hypothetical scenario - to fill out the probability of performing an activity in the given situation. These probabilities were subsequently used to estimate the utilities by means of a binary logit model. It should therefore be stated that only a specific case of the Aurora model is tested. The utilities and the estimated parameters were observed for two different activity types, i.e. "Social Visit" and "Daily Shopping" in order to examine whether activity-specific dependencies could be observed. In order to isolate the effects of the different aspects that were investigated in this paper (i.e. duration, history, location, time of day, presence of accompanying persons and gender), fraction-utilities were estimated using the theory of the S-shaped utility functions.

The data that were used for this research were collected using a dynamic Internet-based application, which enabled personalizing the hypothetical scenarios for each respondent so he/she could easily recognise himself/herself in the presented situation. Additional advantages of using a computer based survey are the reduced cost of the data collection and the immediate availability of the gathered information.

In future research the detailed S-shaped utility functions, which are obtained using the procedure described above, will be applied in a scheduling model.

This introduction constitutes the first part of this paper. In the second part the state-of-the-art of activity-based scheduling models is shortly presented. Thirdly, the theory behind S-shaped utility functions is explained and the most important differences with other utility-based approaches are highlighted. The fourth section includes the stated-preference method that was used for present research and elaborates the followed estimation procedure. The survey design and implementation constitute the fifth part of this document. Finally, the most important research results are presented. Suggestions for further research and the core conclusions finish off this paper.

## 2. Activity-Based Within-Day Scheduling

Until recently, trip and tour based models were generally used to analyse and predict the transportation choices made by individuals. Nowadays the activity-based approach has convinced many researchers of its potential. By applying this approach, the underlying behavioural mechanisms of travel are taken into account: individuals travel around in order to reach the locations where activities can be conducted that cannot be conducted at the home location. The activity-based approach captures individual travel behaviour more realistically than tour or trip based models and is therefore increasingly being applied in transportation research. (e.g. Bhat et al., 2004)

Improvements in understanding how and why people implement activities during a day are necessary, as more accurate forecasts and more precise policy evaluations are demanded. The still limited insight in the daily activity schedules that consist of the activities and travel episodes an individual implements, has incited researchers to study the scheduling process more thoroughly. (e.g. Arentze and Timmermans, 2000; Roorda and Miller, 2004). In addition, within-day rescheduling behaviour has become a focus of attention (Gärling et al., 1999; Timmermans et al., 2001; Joh et al., 2002) However, this research has just scratched the surface and therefore still little is known about within-day rescheduling caused by e.g. unexpected events or time pressure. Present research is therefore aimed at elaborating and especially operationalizing the Aurora model that explains how individuals change their activity schedule during the day. The model is based on the utility-based framework presented below. Insight into the complex and reciprocal relations between the schedules' attributes are important, because in evaluating the impact of policy measures on travel behaviour, it is not relevant to examine how the measures affect a single activity or travel attribute. If policy measures are implemented, they will obviously affect the complete activity schedule and evaluations of the proposed measures have to take this complex framework of activities and travel episodes into account. (Arentze et al., 2005; Joh et al., 2005)

## 3. S-Shaped Utility Functions

Individuals derive a certain level of utility - directly or indirectly and consciously or unconsciously - from participating in all sorts of activities and their scheduling and rescheduling decisions will be mainly driven by the experienced utility. Although utility is an abstract concept that cannot be observed nor measured, it is possible to design a utility function that computes a numerical value based on a set of activity characteristics, such as e.g. activity type, duration, time of day, etc. Other situational aspects that are relevant for the utility and individual attributes of an activity (e.g. location, travel time, travel mode, etc.) can also be incorporated in the utility function. The resulting numerical value is then associated with a particular utility level (Ben-Akiva and Lerman, 1985).

Although utility theory, which has its foundations in micro-economic theory, has successfully been used in transportation research to model diverse discrete choice processes, there is no theoretical consensus on the best shape of the utility function for activity duration. While some scholars advocate a utility function with an ever-diminishing marginal utility (e.g. Kitamura et al., 1996; Bhat, 1999), the present study follows Joh et al. (2003) in their argumentation for within-day scheduling based upon an S-shaped utility function. The basic functional form of the S-shaped utility functions suggested by Joh et al. (2003) can be expressed as:

$$
\begin{equation*}
U_{a}=U_{a}^{\min }+\frac{U_{a}^{\max }-U_{a}^{\min }}{\left(1+\gamma_{a} \exp \left[\beta_{a}\left(\alpha_{a}-x_{a}\right)\right]\right)^{1 / \gamma_{a}}} \tag{1}
\end{equation*}
$$

where,
$\mathrm{x}_{\mathrm{a}}$ is the activity duration;
$\mathrm{U}_{\mathrm{a}}{ }^{\text {min }}$ is the asymptotical minimum utility of the activity;
$\mathrm{U}_{\mathrm{a}}{ }^{\text {max }}$ is the asymptotical maximum utility of the activity;
$\alpha_{a}, \beta_{a}$ and $\gamma_{a}$ are activity-specific parameters for the $\mathrm{U}_{\mathrm{a}}$-function.

As the functional form of the S-shaped utility function in Figure 1 clearly demonstrates, activity utility is assumed to increase as duration increases. Activity duration is closely connected to the available time on the moment an individual considers performing an activity: if the available time is too short in comparison with the minimal required duration, the
activity will not be scheduled. The positive correlation between the available time and the utility is obvious: as more time becomes available, the activity duration can be spread out up to its optimal level and thus activity utility will increase. The crucial difference with the logarithmic utility function is the fact that the marginal utility only decreases after a certain amount of time units are spent, i.e. after a particular activity duration is reached. This activity-specific duration is expressed by $\alpha_{\mathrm{a}}$, the inflection point of the utility function. As long as the duration does not exceed $\alpha_{\mathrm{a}}$, a higher utility is associated with each additional amount of time an individual spends on the activity; once the duration exceeds the value of $\alpha_{a}$, the utility increases at a decreasing rate until the upper limit $\mathrm{U}_{\mathrm{a}}{ }^{\text {max }}$ is approached. (Joh et al., 2003)


Figure $1 \quad$ S-shaped utility function with respect to activity duration

As argued, scheduling decisions are complex choices with a variety of behavioural and situational aspects that affect the final schedule. Activity history, for example, refers to the time elapsed since the last time an activity has been performed. Although activity history is rather a situational characteristic than an activity attribute, it goes without saying that the impact on activity utility cannot be ignored: the longer the elapsed time since an activity was last performed, the higher the utility will be when the activity is implemented again. Intuitively, a clear positive correlation between the activity history and utility can thus be assumed, which can be expressed by a similar diagram as the function for duration in Figure 1. In spite of this obvious relation, most other utility-based approaches generally do not include activity history in their theory. In order to overcome this restrictive factor of existing approaches, Joh et al. (2003) converted the upper limit $\mathrm{U}_{\mathrm{a}}{ }^{\text {max }}$ into a variable parameter which is determined by other activity or situational attributes such as e.g. activity history, location and time of day. This innovation with respect to other scheduling models allows capturing the underlying behaviour of scheduling more realistically. (Joh et al., 2003; Arentze et al., 2005)

Arentze et al. (2005) proposed following functional form:
$U_{a}^{\max }=f\left(I_{a}\right) f\left(L_{a}\right) f\left(Q_{a}\right) \frac{U_{x}}{1+\exp \left[\beta_{x}\left(\alpha_{x}-T_{a}\right)\right]}$
where,
$I_{a}$ is the time of day;
$L_{a}$ is the activity location;
$Q_{a}$ is the position of the activity within the schedule;
$U_{x}$ is the asymptotical upper limit of the $U_{a}{ }^{\text {max }}$-function;
$T_{a}$ is the activity history;
$\alpha_{x}, \beta_{x}$ and $\gamma_{x}$ are activity-specific parameters for the $U_{a}{ }^{\text {max }}$-function.

The impact of the activity's position within the schedule on the utility of the activity cannot be meaningfully interpreted outside the framework of the schedule and this paper will therefore not take this element into account. Joh et al. (2005) described the findings that activity location was much less frequently modified than activity timing and duration. This might suggest that people have strong preferences for certain locations. Therefore, it is assumed that the utility of an activity will be significantly higher if the preferred location is chosen. Time of day is also expected to have an additive effect on the utility: irrespective of activity history or duration, utility will be higher during those parts of the day that are suitable to conduct a certain activity. The tentative findings of Joh et al. (2005) indicate that activities performed during the morning period are less frequently rescheduled. Finally, activities involving a larger number of accompanying persons will be less frequently rescheduled. (Joh et al., 2005) This implies that for certain activities the utility will be higher if accompanying persons are present and the utility will decrease if the individual has to perform the activity alone.

The theory of the S-shaped utility functions cannot be applied to all activities, as one takes the wider frame of within-day scheduling into account. Firstly, there are several long-term commitments that individuals choose to fulfil, such as e.g. work, education, etc., which are generally defined by a fixed duration, a fixed location and a fixed time of day. These activities will rarely be rescheduled. Secondly, there are routine activities that are not taken into consideration when an activity schedule is revised, because people perform these activities almost unconsciously or because they are so used to performing the activity always in the same way, e.g. driving children to school, going to the bakery in the morning, etc. The situational attributes or activity characteristics will hence not affect the implementation of these activities. Finally, there are impulsive activities which are unfortunately very hard to
capture in a model. Although the impact of these activities on a day's schedule can be very large, it is not possible to explain these spur-of-the-moment decisions by the S-shaped utility functions. Because these activities do not occur frequently in an individual's schedule, the activity history will not affect the utility in the same way as for more regular activities. It follows that S-shaped utility functions can be applied to flexible non-routine activities that are conducted on a frequent basis, like for example shopping, going out, etc. (Joh, 2004)

## 4. Estimation Procedure

The complex functional form of the presented utility theory makes it hard to validate the approach. Previous studies based upon the S-shaped utility functions used complex techniques like e.g. genetic algorithms (Joh et al., 2003; Joh, 2004) and micro-simulation (Arentze et al., 2005). Following Nijland et al. (2006), a different approach was utilised in the present paper: instead of looking at the S-function in its entirety, the utility of particular data points can be examined. If one looks at the utility for a specific activity in a particular situation (e.g. situation $J=$ activity $A$ conducted alone with duration $D$, history $T$ at time of day $I$ and location $L$ with an available discretionary time $V$ ) the utility for A consists of the fraction-utilities produced by the different attributes at the specific levels $D, T, I, L, V$ and 'alone'. This can mathematically be expressed by the following function:

$$
\begin{equation*}
U_{a_{j}}=\sum_{j=1}^{n} X_{j} \tag{3}
\end{equation*}
$$

where,
$U_{a j}$ is the utility of activity $A$ in situation $j$;
$X_{j}$ is the fraction-utility produced by activity-attribute $X$ at the specific level of situation $j$.
$U_{a j}$ is therefore a simple linear function of the fraction-utilities. One has to take into account that $U_{a j}$ is only meaningful in comparison to the utility generated by the same activity in other situations. Only then it is possible to isolate the fraction-utilities of the different attributes. The only remaining problem is the fact that utility cannot be observed nor measured, but the values of the attributes that compose the fraction-utilities can be perceived. As these attributes are the building blocks of the utility function and as the discrete choice theory expresses the relation between utility and probability, it becomes possible to assign utility to the discrete
choice alternatives, in this case performing or not performing the activity. This leads to the binary logit model, which has the following form (Ben-Akiva and Lerman, 1985):

$$
\begin{equation*}
P_{n}(A)=\frac{1}{1+\exp \left(-\mu\left(V_{A n}-V_{N A n}\right)\right.} \tag{4}
\end{equation*}
$$

where,
$P_{n}(A)$ is the probability that activity $A$ is conducted by individual $n$;
$V_{A n}$ is the systematic component of the utility of conducting the activity for individual $n$;
$V_{\text {Nan }}$ is the systematic component of the utility of not conducting the activity for individual $n$; $\mu$ is a positive scale parameter that is arbitrarily assumed to equal 1 .

The systematic component of the utility consists exactly of the summed fraction-utilities of equation (3). The binary logit model allows thus to estimate fraction-utilities for the selected data points. The econometric software package SPSS was used to obtain the parameter estimates for the fraction-utilities by means of an iterative maximum likelihood method with maximum 20 iterations. The standard SPSS values of 0.05 probability for stepwise entry and 0.1 probability of stepwise removal were applied, as was the 0.5 classification cut off. As the estimated fraction-utilities of each chosen data point were obtained, these values were used to assess the influence of the different attributes on the utility.

Figure 1 shows that not all data points of the S-shaped utility function contain the same amount of information on the fraction-utilities: the values of duration around inflection point $\alpha_{a}$ are more important to the scheduling process than the data points for very small or very large duration values. The same remark is applicable for activity history. In order to assess the fraction-utility of these two attributes, the data points that are used in the estimation procedure have to be carefully selected. Because different respondents have different utility functions, it was necessary to classify respondents according to their average frequency and average duration so that the most critical data points for all respondents could be utilised. For both duration and history, five classes were distinguished and for each class, different data points were chosen to be used in the estimation procedure.

As the data points for the estimation procedure were chosen, it was possible to construct a stated preference design. The stated preference design used in the present research could be restricted to 16 hypothetical scenarios, because there are no interactions between different attributes for a selected data point. In each scenario another variable was assigned different levels while the other variables were kept at a fixed level, so that the main effects caused by
the attributes could be independently estimated. Activity duration and frequency were each varied over 5 levels, which depended on the group the respondent was assigned to. An example of the group-specific levels for duration and frequency can be found in table 1. Time of day was assigned the logical values 'morning', 'afternoon’ and 'evening’ and the levels of discretionary time approached an average working day (6 hours), an average half-time working day ( 9 hours) and an average day off (6 hours) respectively.

Table 1 Example of T and D-Groups and Group-Specific Levels

| T-Group | Average <br> Frequency | Group-specific <br> T-Levels |  | D-Group <br> Average <br> Duration | Group-specific <br> D-Levels |
| :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | Activity conducted | 1 day | 1 | Activity takes less | 15 minutes |
|  | more than 73 times | 2 days |  | than 45 minutes | 30 minutes |
|  | per year | 4 days |  |  | 45 minutes |
|  |  | 7 days |  | 60 minutes |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

## 5. Survey design and implementation

A dynamic Internet-based survey was used to collect the data needed in order to validate the S-function theory. In comparison with more traditional survey instruments, such as e.g. personal interviews or paper-and-pencil formats, Internet-based applications have several advantages both in the area of data collection as in the area of data processing. Internet-assisted data collection is less time consuming: all respondents can be contacted by e-mail at the same moment, time-consuming personal interviews are no longer necessary, respondents can fill out the survey simultaneously, delays in the mailing process are highly unlikely, etc. Furthermore, data collection is less expensive: personnel expenses are much lower, printing expenses and other operational costs are strongly reduced or even nonexistent, etc. Internet-based applications also offer clear advantages with respect to the data processing aspect of the survey, one example being the consistency checks that can be implemented in advance in order to enhance data quality. Manual imputation is no longer necessary which saves time and money and prevents human error in the imputation process. Another important advantage of an Internet-based survey is the immediate availability of the data, but overall, the most appealing benefit of an Internet-based application is probably its user-friendliness:
respondents can fill out the survey at home and at their own pace, whenever they prefer. Reducing the respondent's burden in this manner, it might even be possible to overcome one of the largest drawbacks of traditional survey instruments, i.e. the limited degree of reporting. (Arentze et al., 1997)

It could be argued that sample bias is introduced as only individuals with access to Internet are interviewed. Previous studies have indeed demonstrated that some socio-economic classes of society, particularly older-age and lower-education groups, are underrepresented in Internet samples, but it must be noted that exactly those groups are also underrepresented when using more conventional survey instruments. It is therefore more important to assure that a sample is representative in terms of travel behaviour, than in terms of socio-economic characteristics. For lack of sound reasons why Internet users' travel behaviour would be significantly different from the travel behaviour of people that do not use the Internet, a balanced Internet sample could provide useful results. Specifically relevant for this survey, recent figures show that $56 \%$ of Flemish households have an Internet connection at home, while up to $53 \%$ of the Belgian inhabitants surf the Internet at least once a week, indicating that Internet-users are a substantial part of the population. (NIS, 2005; Arentze and Timmermans, 2002)

In order to collect all necessary data, the survey design was rather extensive: in the first part of the survey socio-demographic information was collected through a questionnaire, the second part consisted of several activity-specific questions and 16 hypothetical scenarios concluded the survey. The socio-demographic data (such as e.g. gender, household size, level of education) was collected in order to examine its impact on the S-shaped curves and to allow comparison with other data collection experiments. Furthermore, correct interpretation of survey results is inextricably bound up with the bias caused by the survey method and this bias can also be detected by socio-demographic information.

The questions in the second part inquired respondents about key activity characteristics (such as e.g. duration, frequency, travel time, accompanying persons) for two activities, being "Daily Shopping" and "Social Visit". As mentioned above, not all activities that people perform are relevant for our research. In the present study the activities "Daily Shopping" and "Social Visit" were chosen, because both of them are generally flexible and a large number of individuals conduct these activities on a frequent and regular basis. ${ }^{i}$ The classification of activities was an important aspect in the survey design: the selected categories had to be wide enough to provide useful information and yet limited enough to be homogeneous, so that the gathered data could be analysed in a meaningful way. In order to gather the necessary data to examine the impact of location on the S-shaped utility functions, the respondents were asked
for the two locations they most frequently used to perform each of the activities and all the activity characteristics were inquired for both locations. Respondents that indicated only to visit one location to perform the activity, could immediately proceed the questions about the other activity or to the third part of the questionnaire.

This last part of the survey consisted of 16 hypothetical scenarios, which were designed to collect the stated preference data about the two activities. An exemplary stated preference question looked as follows:
"Assume it is time of day I and today you have $V$ hours of discretionary time. You have $D$ minutes available at present to conduct activity $A$, including travel time. What would be the probability that you choose to conduct the activity immediately (instead of performing it later (later today, tomorrow,...)) on location L1, if it is ... days ago since you last performed activity a?
a) it is T1 days ago
b) it is T2 days ago
c) it is T3 days ago
d) it is $T 4$ days ago
e) it is T5 days ago"

Each situation was twice presented to a respondent: for the same attribute levels the respondent had to indicate the probability that he/she would perform the activity immediately on the second location that he/she filled out for activity A in the previous part of the questionnaire. Respondents were asked to indicate a probability instead of a yes/no answer so that they could take into account other explanatory variables that were not included in the current experiment. In order to make the scenarios as realistic as possible, the activity-specific characteristics that the respondent filled out in part two of the survey were used to design personalised scenarios. By means of a dynamic Internet application it was possible to adjust the history and time of day of the scenarios in such a manner that the respondent was presented with situations in which he/she could easily recognize him/herself.

## 6. Estimation Results

### 6.1 S-Shaped Utility Functions for History ( $T$ ) and Duration (D)

The pilot survey administered for the present research was conducted on a small-scale non-stratified sample of 61 individuals ${ }^{\text {iii }}: 68.3 \%$ of the respondents are women and $31.7 \%$ men. Respondents were selected from the authors' circle of acquaintances and contacted by e-mail. They were also asked to forward the received information to other people who might be interested in filling out the survey. Survey composition reveals that higher-education groups are overrepresented in the sample, while older-age groups are underrepresented: $70.5 \%$ of the respondents had a college or university degree and merely $1.6 \%$ of the respondents was over 60 years old. The average age of the respondents amounted only to 35 years. These biases are obviously due to the recruiting system and the applied survey method probably contributes to the underrepresentation of older-age and lower-education groups. Five respondents indicated for "Social Visit" that they did not conduct the activity and five other respondents stated that they never performed the activity "Daily Shopping", resulting in a sample size of 54 respondents for both activities. It is important to mention that considering the size and composition of the sample, the results that are presented here must be interpreted with caution as they are not representative for the envisaged population. Nevertheless, they are meaningful in that they instigate the validation of the presented utility functions for Belgian respondents.

As mentioned above, the classification of activities was an important aspect in the survey design: useful information can only be provided by activity categories that are sufficiently wide, while at the same time the categories have to be limited enough to be meaningful. It is concluded that "Daily Shopping" is a well-chosen category. The activity characteristics are parallel to the results of a large-scale time use study (NIS, 2002) that was conducted in Belgium in 1999. For example, the average duration for "Daily Shopping" in the present study is 48 minutes compared with an average of 51 minutes for a similar shopping activity in the time use survey. ${ }^{\text {iii }}$ Some of the present study's findings seem to indicate that the activity category "Social Visit" is less suitable for the validation of the S-function theory: "Social Visit" has an average duration of 249 minutes which is very high, compared to the 119 minutes average duration of the (broader category of) social activities in the time use survey. ${ }^{\text {iv }}$ Furthermore, a high standard deviation of 474 minutes was registered, which is not comparable to the acceptable standard deviation of 24 minutes for "Daily Shopping". But if one takes a closer look at the data, there are 3 respondents that indicate to perform the activity
"Social Visit" for more than 15 hours. Follow up interviews with those people reveal that they visit for at least a full day and mostly stay over for at least one night at the friends or relatives they visited. The standard deviation for the reduced sample of 51 individuals falls to a much more acceptable 88 minutes. Furthermore, over 70\% of the respondents interpreted "Social Visit" as a visit to a close relative (son/daughter, parents or grandparents): findings which are not in line with a heterogeneous activity category. Obviously, this means that the results presented here cannot be generalised to all social activities, as the examined subclass consists of the most significant and frequent social contacts.

The S-shaped utility functions for activity duration and history were fitted on the estimated fraction-utilities for each individual and for each group. Figure 2 shows the resulting duration and history function for the different groups of the activity "Social Visit": the expected positive correlation between activity utility and duration is apparent, as is the positive relation between utility and history. The resulting $T$-functions indicate that the selected groups and levels were meaningful, but the overlaps in the $D$-functions seem to add prove to the non-optimal choice of the activity category "Social Visit". Finally, the utility functions have obviously no linear shape and especially in the history graph, a clear S-shape can be distinguished.



Figure $2 \quad$ Measured impact of $D$ and $T$ on the utility of "Social Visit"

Figure 3 visualises the same curves for the activity "Daily Shopping". From the duration graph it shows that all respondents were assigned to the 2 D -groups with the smallest average duration. The small size of the used sample is probably the most important cause for the lack of respondents in groups 3 to 5 , but further investigation might be needed to make sure the duration groups are meaningfully categorised. From the history graph it can be deducted that there is no linear relation between history and utility, but the S-shape of the duration function is less obvious.


Figure 3 Measured impact of $D$ and $T$ on the utility of "Daily Shopping"

### 6.2 The Impact of Time of Day (I) on S-Shaped Utility Functions

The fraction-utilities of I represent the impact of time of day on the utility of an activity. It is observed that 'evening' is the preferred time of day for the activity "Social Visit" with $52 \%$ of all respondents indicating they only visited friends or relatives in the evening period. As was expected, the utility of the time frame people prefer, is mostly higher than the utility of other periods during the day. Most respondents indicated for example that they prefer conducting the activity "Social Visit" during the evening period to rescheduling the activity to another day. A likely cause for these findings is the fact that the respondent might take into account the uncertainty about the other person's schedule. Alternatively, it might be possible that the double constraint of the working situation of the respondent in combination with the working situation of the visited person prevents the activity of being rescheduled. The preferences of 'evening' respondents are graphically presented in Figure 4 for the activity "Social Visit" and the resulting stepwise function corresponds to the expected additive effect of time of day on the utility function.

Analogous results are obtained for the activity "Daily Shopping", although less respondents preferred time of day 'evening' for "Daily Shopping": $43 \%$ of the total sample. For the full-time working respondents this number increased until $61 \%$. It was observed that the majority of people indicating 'morning’, 'afternoon’ or 'evening’ as their preferred time of day to conduct "Daily Shopping", experienced a higher utility for these day parts.


Figure 4 Measured impact of $I$ on the utility of "Social Visit"

### 6.3 The Impact of Location on S-Shaped Utility Functions

Respondents were asked in the survey to fill out information about the two locations where they most frequently performed the two considered activities. Findings reveal that the location of the activity "Social Visit" is closely connected to the people that are visited by the respondent: for all respondents the second location was the home location of a different relative or friend than those visited at the first location. A comparison between the change in activity utility due to location is in this case not relevant. Instead of comparing locations, one would be comparing subtypes of activities.

For the activity "Daily Shopping" it is possible to meaningfully interpret the visited locations: $72 \%$ of the respondents that performed "Daily Shopping" on a regular basis indicated that they also visited another location frequently. Although the shapes of the resulting utility functions differ in steepness, inflection point and symmetry over different respondents, the overall conclusion is that for a specific duration the utility associated with location 1 is higher than the utility for location 2 . The $D$-functions of two exemplary respondents are plotted in Figure 5 for the two locations these individuals visited when conducting the activity "Daily Shopping". The utility functions have a distinct S-shape and an additive shift can be observed from one function to the other following the argumentation proposed earlier.


Figure 5 Measured impact of location choice on the $D$-function for "Daily Shopping" for two different respondents

### 6.4 The Impact of Accompanying Persons and Gender on S-Shaped Utility Functions

A dummy variable that represented the presence of accompanying people, was inserted into the applied binary logit model, so that the effect of other people jointly conducting the activity "Social Visit" or "Daily Shopping" with the respondent could be measured. As can be observed from Figure 6, there is a different impact for the two activities. The utility of "Daily Shopping" is higher when the activity is performed alone, although the estimated effects differ only marginally. The utility of "Social Visit" is substantially higher when other people are involved, indicating that this is typically an activity that people prefer to conduct together.


Figure 6 Measured impact of accompanying persons on the $D$-function of "Daily Shopping" and "Social Visit"

The measured impact of gender on the utility functions is less obvious. Depending on the T-groups and D-groups and on the activity type, different effects are measured. These can be caused by the scale of the pilot sample and further research is therefore necessary to assess whether gender and other socio-demographic data are relevant for the shape of the utility function.

## 7. Conclusions

The analyses reported in this paper are part of a wider research programme, which aims at developing the FEATHERS model. This model can best be viewed as an elaboration of Aurora (Joh, et al., 2002, 2004, 2005). Aurora is based on assumed S-shaped utility functions, but the validity of these functions has only been tested in a limited sense once (Nijland, et al., 2006). This study constitutes an elaboration and extension of this previous study, although using the same methodology. In particular, the effects of duration and history were examined on the gathered stated-preference data. Additionally, the impact of location, time of day, accompanying persons and gender was studied.

Results indicate that the used theory of S-shaped functions can be defended: the expected correlation between activity duration and utility and between activity history and utility were observed, even within the small scale sample used in this research. Furthermore it can be concluded that the additive effect of time of day, location and accompanying persons in effect do exist, although further research is necessary to assess the magnitude of these effects. The impact of these attributes was also found to be activity-dependent, indicating that it is necessary to classify the activities by type, although the effect of other activity classes than the ones used in this paper, can be examined. Socio-demographic data were not found to be uniquely affecting the $S$-shaped utility functions.

## Endnotes

${ }^{\text {i }}$ Average participation rate for "Daily Shopping" on Saturday equals 47.13\%; average participation rate for "Social Visit" on Saturday amounts up to $76.88 \%$ and on Sunday even to 79.02\%. (NIS, 2002)
${ }^{\text {ii }}$ After data processing: the webpage of the survey was visited 105 times, the first questions were answered 88 times and 61 respondents completed the survey.
iii Average duration per participant on a weekday for the activity "Daily Shopping". (NIS, 2002, p.29, Table B.1)
${ }^{\text {iv }}$ Average duration per participant on a Saturday for the activity "Social Contacts".
(NIS, 2002, p.43, Table B.1)

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