CAPTURING SHORT AND LONG TERM DYNAMICS OF ACTIVITY TRAVEL BEHAVIOR: DESIGN OF A STATED ADAPTATION EXPERIMENT

Psarra Ifigenia, Urban Planning Group, Eindhoven Technical University, I.Psarra@tue.nl

Arentze Theo, Urban Planning Group, Eindhoven Technical University, t.a.arentze@tue.nl

Timmermans Harry J.P., Urban Planning Group, Eindhoven Technical University, h.j.p.timmermans@tue.nl

ABSTRACT

Whereas the focus of transportation policy used to be on expanding and improving the supply side, nowadays it is on managing the demand for transportation. This implies that individual choice processes become increasingly important and exactly these processes are ideally examined by means of stated adaptation experiments. Stated adaptation experiments can be elaborated in order to collect data on how people change their activity-travel patterns when faced with new constraints or new information, as respondents indicate their stated responses to a hypothetical scenario. On the other hand, dynamic models simulate behavioural response to endogenous or exogenous change along various time horizons. Prior research has predominantly addressed a specific kind of change, usually affecting a specific time-horizon. The current study focuses on a dynamic model of activity-travel decisions which links short and long-term adaptation decisions in a hierarchical manner. We consider both a top-down chain of influence, where life-trajectory affects daily activity agendas, and a bottom-up process, where problems with rescheduling on a daily basis may induce a change even in lifecycle level. The developed model focuses on the bottom-up, endogenous dynamics and their impact along various time horizons. The design of a stated adaptation experiment in order to validate this model and the way that various special demands of this data collection, have been tackled, are described in this paper.

Keywords: stated adaptation survey, activity-travel behavior, endogenous dynamics, stress

1. INTRODUCTION

Now that operational activity-based models of travel demand have been developed in various countries, the academic research agenda has shifted to the challenge of constituting these models dynamic. As it is mentioned in Arentze *et al.* (2000), models based on behavioral change are supposed to be more valid and sensitive to a larger spectrum of policies, plans and designs. Usually, when dynamics are mentioned, three time-horizons are implied: short-term, mid-term and long-term. In Miller (2005), it is explained that the key difference between short-term and long-term adaptations is that the former occurs within the context of specific resources and restrictions (e.g. a current number of household cars, a current residential location, etc), while the latter involves actions that alter these opportunities or constraints. Nevertheless, decision-making processes concerning both types of activities (what to do today in the context of the available resources? Can/should I change my available resources today?) are mutually affected. Specifically, decisions about resources constrain day-to-day activities (top-down chain of influence), while day-to-day experiences “feed back” information about resource needs and opportunities (bottom-up process of influence).

Prior research has predominantly focused either on one type of extrinsic change (e.g. implementation of a specific pricing policy) or at one time-horizon (e.g. the short-term/daily rescheduling behavior). In contrast, the current study focuses on the bottom-up process of influence, where short and long-term adaptation decisions are linked in one decision-making model, in order to trace how daily experiences may trigger a long-term adaptation of the activity-travel habits. In other words, this model predicts when somebody considers conducting a long-term change, due to dissatisfaction with the daily activity-travel practice.

To sum up, the aim of this study is the modeling of dynamic activity-travel decisions by hierarchically linking short and long-term adaptation responses to dissatisfaction with the current activity-travel experiences. In order to develop such a model, a large dataset needs to be collected and analyzed. The goal of the current paper is to share our reflection on which would be the most suitable data collection method. Subsequently, the design of a stated adaptation experiment and the way that various special demands of this data collection, have been tackled, are also described in detail.

In the following, first, there will be a description of the conceptual framework of the model, as well as a mathematical interpretation of it. The reason for this is that we want to make the reader aware of the conceptual framework and the special data needs of this model. At any case, every data collection is carefully tailored according to the specific model that will be estimated based on these data. Second, some discussion on which data collection method would be the most suitable follows. Then, a summary of some closely related research work, where a stated adaptation experiment has been conducted, as well as a presentation of the design of our stated adaptation experiment is described. The paper is completed with some conclusions and discussion on future work.

2. THE MODEL

2.1 THE ACTIVITY LIST

It is assumed that the activity repertoire of an individual is given by a list of *i* activity profiles $A_i = \{A_1, A_2, A_3, ..., A_N\}$. The list specifies the type of activities that an individual optionally can perform, as well as the corresponding activity attributes. Specifically, an activity list can contain information regarding the activity type, the location, the start-time, the origin location of the trip, the transport mode used for the trip and the route that is followed (Arentze et al., 2007). All these choices constitute an active profile, which is actually a script of activity travel behavior. For instance, two activity profiles, belonging to the activity list of an individual can be the following:

A_1: Shopping, city centre, start time at 10:00, starting from work location, bike, route A

A_2: Shopping, supermarket, start time at 17:30, starting from home, walking, route B

An activity list includes all the feasible activity profiles that an individual can perform. In other words, an activity list is the exhaustive list of all the possible combinations of activity facets that are available to an individual. Therefore, it is a list of the possible options that an individual can choose and not the list of his/her current habits. Undoubtedly, an individual cannot be aware of and consider all these activity profiles when (s)he has to make a choice, at time *t*. Actually, only a subset of all these options is taken into account, and this subset of activity profiles is defined as the choice–set of the individual at time *t*. Of course, a choice-set is dynamic, as new activity profiles can be added at every time step, while at the same time, some other activity profiles may be discarded, due to memory capacity limitations.

2.2 COGNITIVE AND EMOTIONAL VALUES OF ACTIVITY PROFILES

Endogenously triggered dynamics are intimately related to the formation of choice-sets. Han et al's work (2007-2010) on choice-set formation constitutes one of the basic underpinnings of the model described in this paper, despite the fact that it mainly concerns shopping activity type and focuses on location choice-sets. Specifically, it is regarded as the basic mechanism that can be further extended and elaborated, in order to construct a model that takes into account (i) all the activity types that may be included in an individual's agenda and (ii) most of the activity attributes that are considered when making a choice. Summing up, the model introduced in this section is based to a great extent on the work of Han et al. (2007-2010).

The expected utility of an activity profile i, of activity type k, equals to:

$$EU_{i_k}^{t} = EU_{i_k}^{static} + EU_{i_k}^{dynamic,t} \tag{1}$$

$$EU_{i_k}^{static} = \sum_j \sum_n \beta_{jn}^{static} X_{jn} I_{i_k j}(x_{jn}) \tag{2}$$

$$EU_{i_k}^{dynamic,t} = \sum_j \sum_n \beta_{jn} X_{jn} P_{i_k j}^{t}\left(x_{jn} \mid c_t\right) \tag{3}$$

where:

$EU_{i_k}^{static}$ is the expected partial utility of a profile i_k for static activity attributes *j* under state *n*,

$X_j^{static} = \{x_{j1}, x_{j2}, ..., x_{jN}\}$ are the activity attributes which are temporally invariant,

β_{jn}^{static} is the individual's preference regarding state *n* of static activity attribute *j* and

$I_{i_k j}(x_{jn})$ equals to 1 if the state *n* of the static activity attribute *j* is included in the profile i_k, otherwise equals to 0.

$EU_{i_k}^{dynamic,t}$ is the expected partial utility of activity profile i_k, for dynamic activity attributes under possible states x_{jn} in condition c_t and time *t,*

$X_j^{dynamic}$ are the dynamic activity attributes (e.g. Travel Time, Crowdedness, etc),

β_{jn} is the individual's preference regarding dynamic activity attribute *j* with state *n* and

$P_{i_k j}^t(x_{jn} \mid c_t)$ is the conditional, time-varying probability distribution across $X_j^{dynamic}$ at time *t.*

c stands for condition variables (4 context-condition profiles are considered based on whether it is weekday or weekend and rush or non-rush hour). The more even the probabilities are spread across possible conditions, the larger the uncertainty and vice versa.

However, when an activity profile is implemented, the individual experiences the actual state of each activity facet, therefore the actual experienced utility of an activity profile *i* at time *t* is expressed as:

$$AUT_{i_k}^t = \sum_j \sum_n \beta_{jn} x_{jn} I^t(x_{jn}) + \varepsilon_{i_k}^t \tag{4}$$

$I^t(x_{jn})$ equals 1, if the state *n* of the activity facet *j* was experienced, otherwise equals to 0,

$\varepsilon_{i_k}^t$ is the surprise experienced by an individual at time ***t.***

Nevertheless, if there is a difference between the expected utility and the experienced utility, negative or positive emotions of this experience emerge. The emotional value of an experience event of activity profile i_k at time *t* is:

$$R_{i_k}^t = AUT_{i_k}^t - EU_{i_k}^t \tag{5}$$

If the activity profile has been experienced several times, the emotional values of the experiences will be accumulated and result in a positive or negative overall affective value, associated with the activity profile. The emotional value of activity profile i_k at time *t* equals:

$$E_{i_k}^t(c) = \begin{cases} (1-a_1)E_{i_k}^{t-1}(c) + a_1 R_{i_k}^{t-1} & ,if\ I_{i_k}^{t-1}=1 \quad and \quad I_c^{t-1}=1 \\ (1-a_1)E_{i_k}^{t-1}(c) & ,otherwise \end{cases} \tag{6}$$

0≤ a_1 ≤1 is the trade-off between accumulated past emotional values and the recent ones.

Finally, the overall expected utility of an activity profile i_k at time *t* (including both a cognitive and an emotional component) can be expressed as follows:

$$EUE_{i_k}^t(c) = (1-a_2)EU_{i_k}^t + a_2 E_{i_k}^t(c_t) \tag{7}$$

where: 0≤ a_2 ≤1 is an agent-specific trade-off between rational behavior (based on expected utility) and affective behavior (based on emotional value).

2.3 CHOICE-SET FORMATION

Dynamics on the level of awareness of the activity profiles are contingent on the event memory of the activity profiles and follow the processes of memory decay and refreshment. The conditional awareness level of activity profile i_k at time *t* equals to:

$$S_{i_k}^{t}(c) = \begin{cases} \max(\lambda_1 S_{i_k}^{t-1}(c), \left|R_{i_k}^{t-1}\right|) & ,if\ I_{i_k}^{t-1}=1 \quad and \quad I_c^{t-1}=1 \\ \lambda_1 S_{i_k}^{t-1}(c) & ,otherwise \end{cases} \tag{8}$$

where: $0 \le \lambda_1 \le 1$ is the awareness retention rate (the speed of memory fading),

$I_{i_k}^{t-1}$ equals to 1 if the profile *i* of activity *k* was implemented at time *t*-1, otherwise equals to 0.

I_c^{t-1} equals to 1 if the condition *c* was experienced at time *t*-1, otherwise is equal to 0.

At every time *t*, a choice-set will consist of those activity profiles whose awareness level exceeds a threshold, reflecting limited human memory retrieval. The choice-set for activity type *k* and condition *c* can be expressed as:

$$\Phi_k^t(c) = \{i_k(c) \mid S_{i_k}^t(c) \ge \omega\} \tag{9}$$

where: *ω* is the minimum awareness level for event memory retrieval ability (Figure 1).

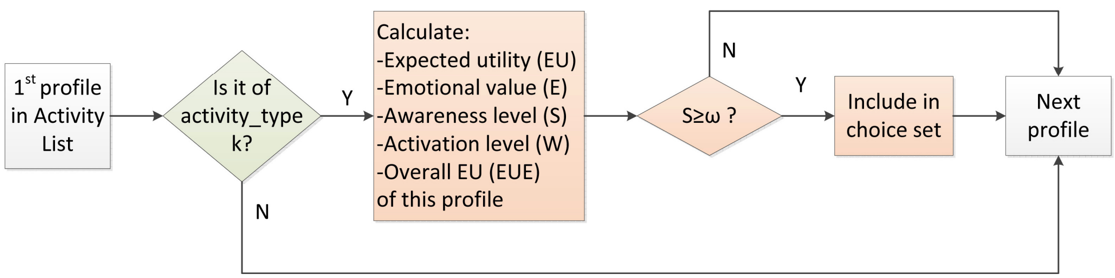

Figure 1: Calculating an agent's choice set for activity k, at time t and under condition c.

2.4 ASPIRATION LEVELS

Herbert Simon (1959) claimed that in order to predict the dynamic behavior of an adaptive organism in a complex and rapidly changing environment, we must also know a great deal about its internal structure and its adaptation mechanisms. He regards economic man as a satisficing[1] animal, whose problem solving is based on search activity to meet certain aspiration levels, rather than as a maximizing animal whose problem solving involves finding the best alternatives. Models of satisficing behavior are richer than models of maximizing behavior, because they treat not only equilibrium, but the method of reaching it as well.

Individual's aspiration levels serve as a subjective reference point of satisfaction and are dynamic and context-specific. Let an individual's current long-term decisions be denoted as *h.* In the context of this study, residential and work location, working times and days (full-part

[1] "Satisficing" was the term selected by Herbert A. Simon to refer to a mode of decision making that he viewed as more realistic than the "maximizing", ordinarily postulated in economic theory and related areas of social science.

time job), car and public transport card ownership are taken into account. Then, we can define $U_k^*(c) \mid h$, as the conditional (taking into account these long-term decisions) aspiration level of activity type *k*, under condition *c.* This means that the constraints, as well as the opportunities that derive from these decisions are taken into account when an individual formulates these conditional aspiration values. On the other hand, $U_k^*(c)$ is defined as the unconditional aspiration level of activity type *k*, under condition *c.* This aspiration value is irrespective of this context of the current long-term decisions of an individual, and therefore not affected by the compromises that may be derived by the restrictions that these decisions induce in the activity-travel repertoires of this individual (Figure 2).

Timmermans *et al.* (2002), Salvani *et al.* (2005) and Habib *et al*. (2006) recommend the use of the term stress, when a discrepancy between the desired and the experienced utility occurs. In the current study, we define stress as the discrepancy between the overall expected utility $EUE_{i_k}^t(c)$ and the conditional aspiration value $U_k^*(c) \mid h$. Many factors may lead to such discrepancies: urban and transport systems are highly dynamic and uncertain; individual needs may differentiate, etc. The performance of the transport or land-use system may decrease below the conditional aspiration level, resulting in search for other alternatives.

Nevertheless, people often are unable to “act at the margin”, i.e. in many situations people do not make perpetual adaptations to their choice behavior, in order to keep themselves at their “optimal” (utility-maximizing) state (Sarjeant, 1986). Thus, it makes sense to assume that people will tend to remain in their current state (same house, etc.) when stress is below a specific threshold. In other words, they tend to stick on their habitual behavior (Gärling et al. 2003). Stress threshold (σ_1) is a predefined, individual specific parameter, reflecting whether an individual strongly dislikes the mental effort involved in finding better activity profiles and is easier satisfied with the current situation.

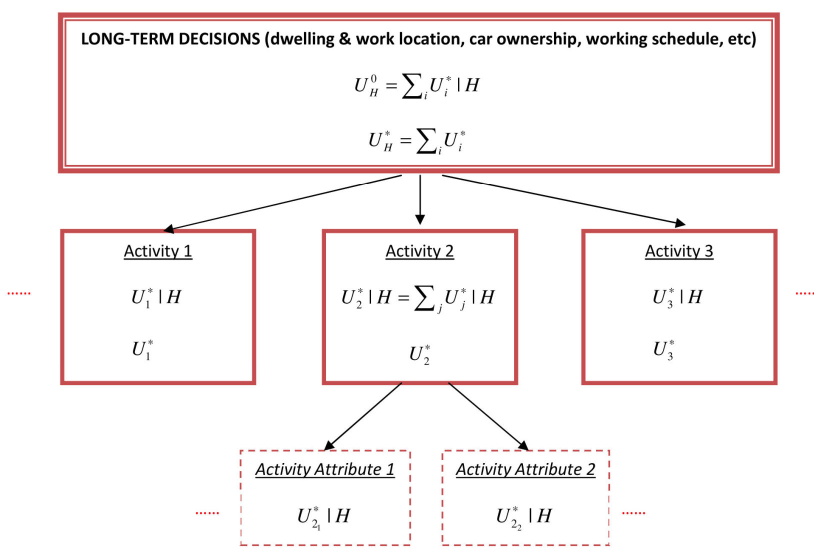

Figure 2 - Diagram depicting the conditional and unconditional aspiration values in the long-term level, activity and activity attribute level.

2.5 MAKING A CHOICE

Almost without exception, everything human beings undertake involves a choice (consciously or sub-consciously). In order to avoid needless mental effort individuals develop habits. Accordingly in our model, an individual is assumed to always first consider the activity profile with the highest activation level in the choice set, which means the activity profile that is most easily retrieved from (action) memory. The outcome of the comparison between aspiration and expected outcome, given current beliefs, determines whether a habitual or a conscious choice will be made. The strength of a trace in memory of actions, called activation level (Han *et al*., 2007), determines whether or not the alternative qualifies as a habitual choice. The activation level of activity profile $i_k(c) \in \Phi_k^t(c)$, at time t equals to:

$$W_{i_k}^t(c) = \begin{cases} W_{i_k}^{t-1}(c) + \gamma AUT_{i_k}^{t-1} & ,if \ I_{i_k}^{t-1}=1 \ and \ I_c^{t-1}=1 \\ \lambda_2 W_{i_k}^{t-1}(c) & ,otherwise \end{cases} \quad , where \quad i_k(c) \in \Phi_k^t(c) \tag{10}$$

where: $0 \leq \gamma \leq 1$ is the recency weight and
$0 \leq \lambda_2 \leq 1$ is the retention rate.

The habitual option can be denoted as $i_k^*(c) \in \Phi_k^t(c)$, which is the profile with argmax $W_i^t(c)$.

If: $$U_k^*(c) \mid h - EUE_{i_k^*}^t(c) < \sigma_1 \tag{11}$$

then the habitual alternative is chosen at time t (Figure 3).

However, in case that this difference exceeds the stress threshold, an individual acts in conscious mode. Only in this case, they will try to find the alternative with the maximum expected utility, among the choice-set that they are aware of at this moment. Han et al. define this process, as an exploitation effort, as the individual will actually search for a better alternative in the current choice-set. Specifically, the activity profile with the highest overall expected utility ($i_k^{**}(c) \in \Phi_k^t$ with argmax $EUE_{i_k}^t$) will be chosen. Therefore, if:

$$U_k^*(c) \mid h - EUE_{i_k^{**}}^t(c) < \sigma_1 \tag{12}$$

then the exploitation alternative is chosen at time *t* (Figure 3).

Nevertheless, in case that this difference exceeds the stress threshold, an individual will start exploring new alternatives, beyond the current choice-set. In that case, a sequential exploration of "increasingly major" changes is assumed to be followed in order to relieve stress. This process of exploration is not random, as it will be guided by the activity facets that caused dissatisfaction. From the perspective of the analyst, who has limited information about the individual, the probability that an individual in exploration mode finds a new activity profile and decides to try it, is specified as:

$$P^t(i_k(c) \mid J') = \frac{\exp(V_{i_k}^t(J')/\tau)}{\sum_{I_k} \exp(V_{i_k}^t(J')/\tau)} \tag{13}$$

where: τ is the degree of information lack about alternatives in the study area.

$$J' = \{ j \mid U_{kj}^*(c) \mid h - eu_{i_k^{**} j}(c) > \sigma_1 \} \forall j \tag{14}$$

are the activity facets of $i_k^{**}(c) \in \Phi_k^t$ that caused dissatisfaction.

$V^{t}_{i_k}(J' \mid c)$ is the utility measure of each activity profile of activity type *k* that belongs to the activity list, but not at the choice set. This utility measure is based on the expected utility of the facets that caused dissatisfaction at time t and under condition *c*.

When people feel satisfied with the new situation, they stop exploring for other alternatives and a new habitual behavior emerges again. It is assumed that an individual will keep a record (N^{t-1}_{k}) of how many consecutive times (s)he already tried exploring a new profile of the same activity type. It is also assumed that as the exploration effort is built up and exceeds a predefined threshold, instead of continuing exploring, the individual will avoid further frustration, by lowering the aspiration level of the activity facets that caused dissatisfaction (realizing that they are not realistic). From the perspective of the analyst, the probability of lowering the conditional aspiration level of a facet $j \in J'$ of activity type *k*, is:

$$P^{t}(lowering\,U^{*}_{kj}(c) \mid h) = \frac{\exp(\mu + \nu N^{t}_{k})}{1 + \exp(\mu + \nu N^{t}_{k})} \tag{15}$$

where: *μ* and *v* are parameters of the logistic function.

When lowering the $U^{*}_{kj}(c) \mid h$, the individual replaces the current conditional aspiration level of the activity facets that caused dissatisfaction with the corresponding activity facet aspiration level of the profile that currently has the highest expected utility.

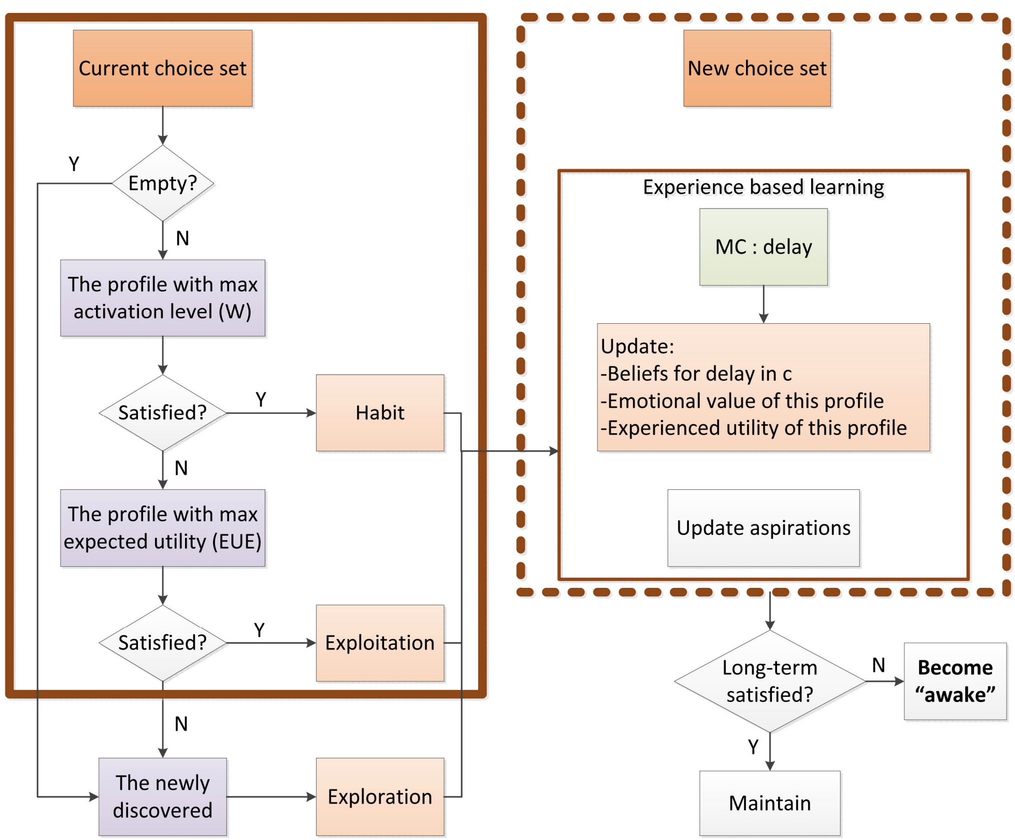

Figure 3: Flow chart, depicting the dynamic process of making a choice.

2.6 DRAMATIC CHANGES

Adaptations can occur in one of the following ways: short-term changes in selected actions within a given set of opportunities and decision rules (e.g. changing commuting travel mode, etc.); long-term changes in the resources available (e.g. purchasing an additional car, etc.). As it is already mentioned, we assume that an individual takes into account the whole bundle of long-term decisions, characterizing their life, when assigning a conditional aspiration value to an activity type. Consequently, the model predicts when an individual gets “awake” and realizes that a long-run, dramatic adaptation should be decided. Becoming “awake” means starting considering that a change needs to be conducted in this context of long-term decisions that characterize somebody’s life. This phase will lead to search behavior (on the long-term level this time), which may result in the decision of implementing one or more adaptations. For instance, change of residential or work location, purchase of a car, adaptation of the working schedule, etc. Of course, the final decision that it would be more preferable to stay in the current situation, is also possible.

The conditional aspiration value of an activity type *k* ($U_k^* \mid h$) can be calculated by weighting across all conditions *c*:

$$U_k^* \mid h = \frac{\sum_c freq_c U_k^*(c) \mid h}{\sum_c freq_c} \tag{16}$$

where: $freq_c$ is the frequency of experiencing condition *c*

Subsequently, the actually experienced utility of the current long-term decisions can be calculated by adding the conditional aspiration values of the *k* related activities:

$$U_h = \sum_k U_k^* \mid h \tag{17}$$

This is for the reason that the conditional expectation values of the activity types are defined in the context of the constraints and the opportunities that the current long-run decisions at the accessibility-mobility domain impose (Figure 2).

The unconditional aspiration value of activity type *k* can be also calculated by weighting across all conditions *c*. Similarly, the unconditional aspiration value for long-term decisions is:

$$U_r^* = \sum_k U_k^* \tag{18}$$

This implies that the expectations of an individual, regarding in general his/her context of long-term decisions, can be estimated by adding the unconditional aspiration values of the activity types (Figure 2). This is because, in that case, the expectations are not restricted by the long-run decisions (current residential and work location, car ownership, etc).

Letting σ_2 be denoted as the stress threshold for the long-term level, we assume that in case:

$$U_r^* - U_h < \sigma_2 \tag{19}$$

the individual does not consider making a long-term change. However, in case of:

$$U_r^* - U_h > \sigma_2 \tag{20}$$

the individual becomes "awake" and starts thinking of conducting a dramatic change at the context of long-term decisions that characterize his life (Figure 4).

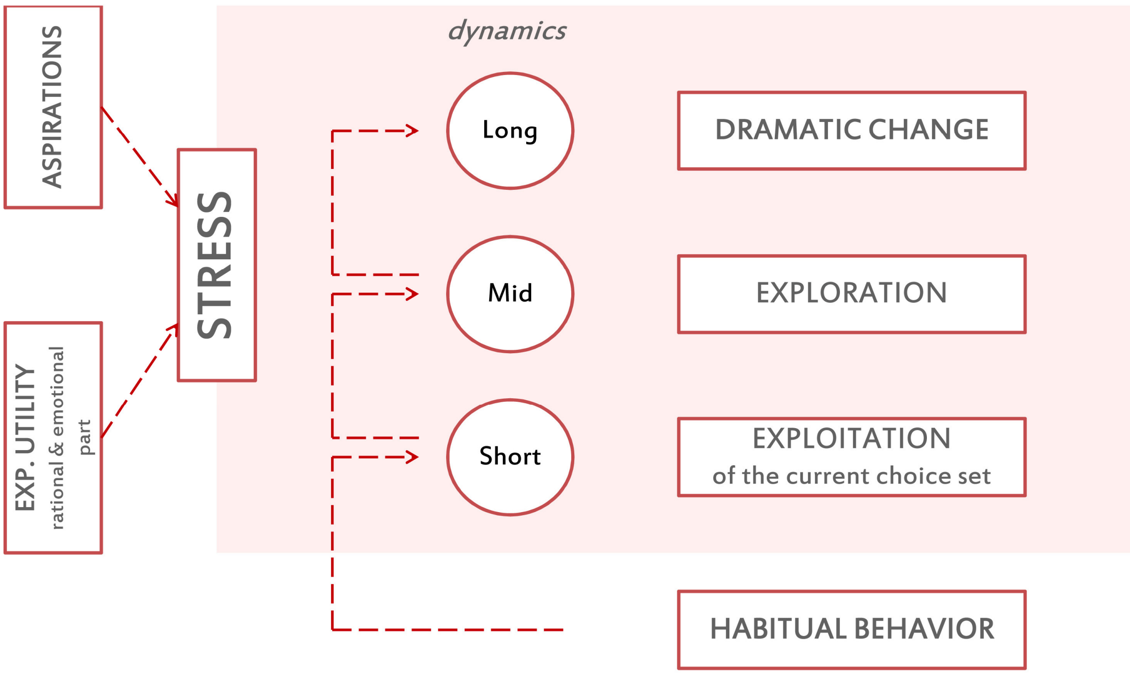

Figure 4 – Graphical representation of the conceptual framework of the model

3. SURVEY DESIGN

3.1. SPECIFIC DATA COLLECTION NEEDS OF THIS MODEL

A special need of this data collection is that we need to measure both the conditional and unconditional aspiration values, which more or less constitute the bifurcation points, after which there will be an adaptation response. Moreover, getting as much as possible information about the choice-set of the respondents is one of the challenges. As far as the adaptation phase is concerned, there should be a process of mimicking a feeling of accumulated stress. Finally, the problem of compressing time has to be taken into account, as this study focuses both on the short and long term time horizon.

3.2. WHICH IS THE MOST SUITABLE DATA COLLECTION METHOD?

The vast majority of the models that have been developed in the past are concerned with the simulation of daily activity patterns and have dealt only marginally, if at all, with dynamics. Specifically, travel choice models are usually developed from *cross-sectional* survey data. These models reflect between-person variation However, Goodwin (1998) claimed that the concept of equilibrium is acting as a barrier to sound policy advice and recommended that attention should be placed on dynamic analysis of travel choices.

There are mainly two reasons why dynamics of activity-travel behavior have not been taken into account in the most of the models that have been developed so far: (i) the lack of any sufficiently large continuous data set of long duration (panel data), and (ii) until very recently, the lack of useful theories and integrative, comprehensive modeling approaches. Available data relate to one or two days observed activity-travel diaries (cross-sectional data), and therefore any advanced dynamic analysis and modeling is not permitted.

Panel data involve repeated observations over time for the same individuals and can be used as an alternative basis for developing travel choice models. As it is mentioned in Chaterjee (2011), panel data can provide information about both current and past circumstances and habitual behavior. Additionally, the researcher can gain information regarding individual specific error term and random error term. Nevertheless, in most of the cases, such data is too difficult to be gathered, because of the too high time and money cost. Additionally, with this method, we cannot control the system variables. On the contrary, with stated adaptation experiments we can get easier to interpret and more efficient data.

Multi-agent modeling, relatively new in urban planning and transportation research, permits the integration of the different time horizons. In such a model, each individual is represented as an agent. Agents hold beliefs, react to various types of change and schedule their activities in time and space. Thus, a multi-agent approach can integrate concepts, developed in different disciplines, and establish the consistency that is required for analyzing and simulating dynamics. The research gap in this context is how to validate and estimate such models. It is very difficult to collect field data in order to observe the underlying decision process, along both short and long-term time horizon. Therefore, the challenge is how to use other data collection methods in innovative ways. However, the validity and reliability of such data collection methods have not been studied at length yet. Even if these prove to be acceptable, it is unlikely that the validation of any dynamic model of activity-travel patterns will be similar to the validation of static models. New methodological principles need to be developed and discussed. Traditional methodological principles to validate models are typically based on parameter estimation, goodness-of-fit and similar concepts. For complex models, such methodological principles may not suffice and should be further improved.

To sum up, estimating parameters empirically and showing that the model can successfully reproduce empirical observations is for many the ultimate proof of model validity, but this methodological principle is likely not very productive in developing dynamic models of highly complex adaptive, co-evolutionary systems. A possible procedure that could be suggested is developing concepts, theory and alternative model specifications and assessing model performance, first by conducting numerical simulations and then by calibrating the models using empirical data, to the extent possible. That is, if not all parameters can be estimated from experimental data, then one could reside to less rigorous methods of calibration for those remaining parameters.

Retrospective survey may be used to collect empirical data on lifecycle events. This means that respondents are invited to recall events they have experienced in their past and report relevant details of these events, including their timing. The potential benefits of the retrospective surveys are that they do not involve great administrative complexity and time delay in data collection, as panel surveys. On the other hand, because respondents are invited to recall incidents in the past, undoubtedly the reliability of retrospective surveys depends fundamentally on the nature of the phenomena about which questions are asked. In general, it could be stated that individuals build up memory traces about their experiences. Such memory traces will be stronger for those experiences that are more significant to them, e.g., experiences that are unique, dramatic, etc. Thus, forgetting is not uniform. Specifically, details of a given event are difficult to be recalled accurately. Therefore, we expect that it will be difficult to gain a lot of input regarding the stress accumulation process that led to some drastic adaptations in the respondent's life.

Thus, in most of cases, researchers need to rely on experimental-design data, usually collected with *stated response* methods. Depending on the nature of the response, we can distinguish among stated preference, stated choice and stated adaptation experiments. In the first case, the respondent has to rate or rank various options, according to his preferences. In the second case, the respondent has to choose one alternative from a specific choice set that is presented to him/her. Finally, in a stated adaptation experiment the respondent has to imagine a specific scenario that would affect his life and indicate what changes would (s)he conduct in order to adapt to this new situation. If we consider the specific needs of the model of this study, the stated adaptation case seems to be the most suitable. The basic assumption is that individuals and households learn to cope with their environment and by learning, develop a habitual behavior at the level of activity profiles. They implement these habits, until changes in their environment will make them reconsider. A stated adaptation experiment will help at systematically recording data on how individuals may choose between adjusting activity profiles currently belonging to their choice sets, exploring and implementing new activity profiles, or conducting dramatic, long-term changes in the available resources, as a response to the changes implied by the scenarios.

A discriminating feature of stated adaptation models is that they allow for effects of a reference situation on responsive behavior, i.e. reluctance to change an existing pattern of behavior, which is not captured by standard stated choice approaches. Moreover, most stated preference and choice studies have been confined to single choice facets underlying activity-travel patterns. This tradition potentially has weaknesses, as the complex interdependencies of activity-travel patterns have been widely reported, and in fact are the primary reason for developing activity-based analysis in the first place.

4. STATED ADAPTATION METHOD

Compared to stated preference and choice experiments, much less is known about stated adaptation experiments. Specifically, in most stated adaptation experiments, respondents need to check whether a change in a currently non-chosen alternative generates an increase in utility, which is higher than the utility difference between the currently chosen alternative and the changed alternative. In more complex experiments, however, the decision context may (also) change. This is more demanding, in the sense that the changed context may be less or even unfamiliar, implying that respondents first need to interpret the data, cognitively construct the appropriate decision context, apply their current preference and decision strategies in the constructed decision context, mentally simulate the consequences of choice options, judge the consequences and report choices or changes in behavior. Hence, respondents may have difficulties to realistically evaluate the decision context. Nijland et al (2008) mentioned that the respondents indicated that they had to think consciously about decisions usually taken subconsciously because of reinforcement and known conditions. Therefore, the selection of the explanatory variables and the choice of their values has to be carefully considered, the size of the sample has to be large enough to allow for statistically significant outcomes and the survey itself has to be designed in a respondent-friendly way.

Interactive Internet-based surveys are found to be very helpful: such surveys are able to dynamically collect and process personalized data, which can be used to design realistic and statistically sound hypothetical situations, so that each respondent can easily recognize himself/herself in the presented situation (Faivre D'Arcier, 2000). The reduced cost of the data collection and the immediate availability of the gathered information are additional advantages. It could be argued that sample bias is introduced, as only individuals with access to Internet are interviewed. However, for lack of sound reasons why Internet users' travel behavior would significantly differ from the travel behavior of people that do not use the Internet, a balanced Internet sample could provide useful results.

4.1 CONDUCTED STATED ADAPTATION EXPERIMENTS IN SIMILAR STUDIES

In order to extend the initial ALBATROSS model, Arentze et al. (2004) reported the estimation of several discrete choice models, describing the reactions of individuals to congestion pricing scenarios. An activity-based approach was used, meaning that all choice facets of activity patterns were taken into account. The study differentiated between primary and secondary response to policies. A stated adaptation experiment, administered on the Internet, was used to collect the data. Respondents indicated if and how they would adjust the departure time, route, destination, transport mode, and/or trip frequency of the activities they conducted on a regular basis, given particular congestion pricing scenarios. Adaptation choice was modelled using the multinomial logit framework. Because of the structural role of work activities in daily activity schedules of individuals, a separate adaptation choice model was estimated for the work activity. Their Albatross model was then run to simulate any secondary responses that emerge when individuals schedule their activities and travel using the primary responses as input (Arentze and Timmermans, 2005).

Specifically, each respondent was given either a train or a road scenario. A road-pricing scenario had the general form: Assume that vehicle taxation is abolished and a price of *X* cent is to be paid for each kilometer travelled by car on the roads and the times at which there is no congestion and *X+P* cent on the roads and the times at which there is congestion (where *X* and *P* were varied in the experiment). Following the scenario, there is a list of questions asking the respondent to indicate whether and which adaptations he or she would do if the scenario were effective. Before proceeding to the questions about the respondent's response to the scenario, the respondent was asked to indicate the frequency of making trips for each mode and the average distance per trip by the relevant mode (car or train) in his/her current travel pattern for the activity category under concern. So, the respondent had to retrieve from memory his/her current pattern of travel regarding the activity. Based on these data, the system calculated and presented to the respondent the total variable costs of travelling (for the activity), under both the current conditions and scenario conditions.

Thereafter, the type of the questions that were posed to the participants was the following: "Would you, as a consequence of the scenario, choose [adaptation option] for conducting [the concerned activity]? If yes, how often would you choose [adaptation option] per [time period]?" Hereby, one adaptation option was given at a time. The options included: performing the activity less frequently, or more often at home, or more often at a location closer to home, switching to another specific mode, travelling more often together with others (in case of car), changing the route and changing the departure time.

One may argue that giving accurate answers to such a question imposes high demands on the mental abilities/efforts of subjects. However, the researchers expect that in the worst case, where the respondent fails to recall details of the current pattern, the most typical or representative trip for the activity would be recalled. Even in such cases, the answers given are not necessarily invalid, but rather they would relate to the most typical instance of the category. If this most typical instance corresponds to the modal trip for the activity, then we may expect that the systematic error across the sample is still limited and acceptable.

Similarly, Weis et al. (2010a,b), focused on changes in travel behavior in response to changes in generalized costs of travel, using a stated adaptation experiment. The survey consisted of a three-stage approach in which, first, a sample was recruited for participation by telephone. Revealed preference data were collected and based on them, the stated adaptation part was constructed. Changing departure time, mode of travel, order and/or duration of certain activities, cancelling certain activities, or adding additional ones, as well as combinations of these adaptation responses were the respondents' possible reactions to the hypothetical scenarios. The researchers used a series of models to account for the relevant decisions and run them sequentially for forecasting. Multiple Discrete-Continuous Extreme Value (MDCEV) model is at the core of the used models, to predict how respondents compensate the gained or lost time under predefined scenarios. This survey differs from Arentze et al. (2004) in that the complete restructuring of a reported activity pattern is considered, instead of a discrete set of options in the adaptation process. In addition, they focused and formulated the travel time losses or gains rather than the effects of specific policies. The survey tool used in these interviews consisted of a game-like display board, on which the respondents could visualize and test their adaptations. This approach ensures that the implications for all relevant decisions (activity and trip generation, scheduling and chaining; destination, mode and route choice) can be captured according to modelling needs. Last but not least, the recorded reactions to the scenarios relate to the whole schedule rather than to a specific trip, as is often the case in traditional *stated choice* surveys.

5. DESIGN OF THE EXPERIMENT

In this study, the activity-based approach is used; meaning that all choice facets of activity patterns are taken into account, as well as a complete set of activities. Therefore, after the socio-demographic questions at individual and household level, an exhaustive list of activity types is presented to the respondent. Then (s)he is asked to indicate the frequency of making trips for each of these activities. In order to reduce the respondent burden, the activity profiles and the adaptation questions in the remaining part of the survey will focus only on the three activities with the highest frequency. After all, we assume that these activities are the ones that have the biggest probabilities to trigger a long-term change.

At the following stage, we ask about respondent's long-term decisions, in order to help them realize the notion of *h* (main long-term decisions: residence and work location, working days and hours, transport mode availability). Thereafter, questions related to the unconditional aspiration values that the respondent holds for every activity type, are asked. Specifically, the questions refer to travel time, congestion, crowdedness and parking availability under the four context-condition profiles, availability of public transport and travel cost. Here is an example, where the respondent is questioned regarding the unconditional aspiration value that (s)he holds in terms of travel cost: "Try to imagine your life without all these above mentioned decisions and the restrictions they impose. Please indicate for each of the following activities a reasonable amount of money that you would ideally spend in order to access the activity location."

The next phase of the experiment aims at retrieving for each activity type the corresponding activity profiles. The three most frequently conducted activities are processed one by one. An activity profile consists of the following activity attributes:

Location	Start-time	Origin	Mode	Route

The Company during the trip could also be regarded as part of an activity profile, but in the context of this research experiment, is left out of consideration. It should be noted that each activity type can have more than one activity profiles, which vary in terms of the included activity facets: the destination location, the start-time, etc. Hence, the corresponding activity profiles of a given activity type can be more than one, namely as many as the number of combinations of activity attributes, that a respondent usually implements. For example, if the commuting trip is usually conducted on Friday by car and on the rest of the week by bike, there already exist two different activity profiles related to this activity type (going to work). A web-based interactive questionnaire, which is specially programmed for our survey, is used to record respondents' current habitual activity travel patterns. The interactive platform of this questionnaire provides respondents the chance of visualizing the locations where the activities are conducted and also their travel specifications in terms of different modes.

For every activity profile we also retrieve some additional data. The additional data include the Frequency and the Day-of-the-week that the activity profile is conducted. This information does not result in splitting, as it is not part of an activity profile, as we view it. Additionally, for every activity profile, the respondent is asked to indicate the travel time and travel cost that they usually have to spend when implementing it. Also, (s)he has to indicate how congested the streets are usually and to rate public transport and parking availability. In case the mode is a means of public transport, (s)he is asked to indicate how crowded the vehicle is usually. Finally, the frequency distribution among the profiles is also demanded.

In this way, by getting the current activity profiles and the relevant additional information, data are collected on the habitual activity travel patterns of the respondent. This list of habitual activity profiles will replace the travel diary, which corresponds to a specific day, in former studies. Moreover, the respondent is also asked to indicate what other possibilities (s)he sees, in order to get further information about other choices regarding the activity attributes of each activity type and get a better image of the choice set of every respondent.

Then, for every activity type, we summarize and present to the respondent, the choices they make for every activity attribute, as they emerge from their activity profiles. Then we ask them to indicate whether they are satisfied with each of these choices. The "worst" case, with which they are satisfied, constitutes their aspiration value as well. In case they indicate that they are dissatisfied with all of these options, we ask for how long time they are already in this situation, in order to estimate the influence of the amount of time on the level of dissatisfaction. In that case, we also ask about the level of performance they are satisfied with. In this way, we get information about their conditional aspiration values for every activity type, stress threshold σ_1, as well as the preferences (β values) of the activity facets[2].

After having collected all these data regarding their current choice set, their preferences and their aspiration values, we proceed with the adaptation part of the experiment. Unlike former studies, the scenarios assigned to the respondents do not aim at determining the effects of specific policies and they do not focus on only one activity attribute (e.g. travel cost). They are formulated as general as possible, in the following form: "Imagine your reported trip to [Activity] would take [*y*] minutes instead of [*x*]."

The "problem" in the presented scenario will increase three consecutive times, in order to create a feeling of accumulated stress. An example could be asking them to imagine that the travel time of their commuting trip would increase. A possible option could be first assuming that it has increased to a point slightly higher than their aspiration level. Then we can progressively increase the travel time by 50, 100 and 200 percent. In this way, four scenarios can be created. For instance, we could create scenarios where the stress accumulates by gradually increasing the travel time for the bus trip to the work activity from the 20 minutes (which is a value a bit higher than the 15 minutes that constitute their aspiration level), in 30, 45, and 60 minutes. In case that the respondent indicates that (s)he would conduct a long-term adaptation at some point, this process of stress accumulation will stop.

The respondent will be invited to state their likely reactions to each hypothetical scenario that will be presented to them. This is an example of how the adaptation questions will look like:

[2] If we were based only on the revealed data we get from the current habitual activity profiles, we would have only the information about what they currently choose and not what they would like to have.

"Imagine that the travel time for reaching your work location was x minutes (a value slightly higher than their aspiration values). Would you change something in what you currently do (their current habitual activity profiles)?

The respondent has to indicate his/her adaptation choice among the following responses:

- *SHORT-TERM RESPONSE*
    - *a. Change the frequency of the activity type.*
    - *b. Change the frequency distribution of the activity profiles.*
    - *c. Change location of the activity (e.g. conducting the activity at one of the location options that they are aware of, or exploring a new one).*
    - *d. Change the departure time of the trip.*
    - *e. If the activity is conducted only on weekdays, try conducting it during the weekend. And vice versa.*
    - *f. Change the transport mode (to one of the other possibilities they are already aware of, or explore another option that is currently unknown).*
    - *g. Change the origin-location of the trip.*
    - *h. Change the route of the trip (to another one that they have tried in the past, or explore a new one).*

It will be possible to indicate more than one short-term response, as it makes sense that they may try a combination of e.g. transport mode and activity location. Moreover, they will be asked to indicate both their primary and secondary responses. Finally, the respondents will be questioned whether, given these primary responses, they would also consider conducting one of the following long-term adaptations:

– *LONG-TERM ADAPTATION*
    - *a. Change of residential location*
        - *i. Change home location to a location closer to work*
        - *ii. Change home location to a location closer to the city center*
        - *iii. Change home location to any other location. Please specify.*
    - *b. Change of work location (if there is such a possibility)*
        - *i. Change work location to a location closer to home.*
        - *ii. Change work location to a location closer to the city center*
        - *iii. Change work location to some other location. Please specify.*
    - *c. Availability of transport mode:*
        - *i. Purchase of a car*
        - *ii. Purchase of another transport mode. Please specify.*
        - *iii. Purchase of a public transport card. Please specify.*
    - *d. Change of work context:*
        - *i. Change of working hours*
        - *ii. Change from full-time to part-time or vice-versa.*

Thereafter, the stress accumulation process starts, by asking whether they would react in the same way that they have indicated before, or they would try something additional to that, in case that e.g. the travel time for reaching the work location was (1,5*x) minutes.

6. CONCLUSION AND DISCUSSION

The aim of this study is the design of a stated adaptation experiment that allows validation and estimation of the parameters of a model that is able to predict short-term mobility decisions, as well as their impact on long-term decisions, such as residential location, car ownership, etc.. In other words, the circumstances under which an individual considers conducting a long-term change, without being triggered by an external factor (a life-trajectory event or the implementation of a policy) are predicted.

Specifically, the mental and physical mechanisms, based on which an individual selects an activity profile, when an activity is to be carried out, are modelled. Depending on aspiration levels and experiences, this profile can be the one with the highest activation level (habitual choice), the one with the highest expected utility (exploitation choice), or the newly discovered one (exploration choice). Nevertheless, a deviation between the aspirations of an individual regarding the long-term decisions of their life and the actual utility that (s)he receives from them may arise. In case that this discrepancy exceeds a predefined threshold, the individual gets 'awake' and considers conducting a long-run, dramatic adaptation.

The basic advantage of a stated adaptation experiment is that we can manipulate the adaptation conditions, according to our data collection needs. Thus, we can more easily interpret the causal effects of changes, while we avoid the memory matters that may arise with a retrospective survey. On the other hand, the basic disadvantage is that the respondent is asked to imagine a hypothetical situation and we can never be sure that (s)he would react in the same way in reality.

In most stated adaptation experiments, respondents are, first, asked to report particular facets of their current behavior for a certain period of time, and then in a second stage, choice experiments are constructed, based on the information provided at the first stage. The design presented in this paper - of an interactive internet-based survey - differs from previous studies in two respects. First, the design is not based on a certain period of time, but on habitual behavior and the concept of activity profiles. Second, it focuses on the adaptation of these profiles in response to the provided scenarios. Finally, it should be mentioned that this experiment does not aim at investigating the adaptations of individuals, when faced with specific types of policies, but at the revealing and analysis of endogenous dynamics.

Future research could focus on the analysis of the collected data and the calibration and the estimation and validation of the dynamic activity-based model. On a second level, the extension of this model to the household level would be quite interesting. Finally, modelling the way that people explore and take long-run decisions, after becoming "awake" and realizing that the actual utility they receive from the current long-run choices is lower that their expectations, is of high importance, as well.

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