Modeling the Evolution of Dynamics in Activity-Travel Behavior:
Results of Numerical Simulations

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Abstract

The current study aims at developing a dynamic model of activity-travel decisions, which links short and long-term adaptation decisions. Specifically, we consider a bottom-up process, where problems with rescheduling on a daily basis may ultimately induce a change in long-term level. When an individual has to decide how (s)he will travel in order to reach an activity location, (s)he actually implements a specific script. The proposed framework integrates three key concepts, namely aspiration, activation and expected utility. Aspirations represent an individual’s expectation, while activation levels represent the ease with which a script can be retrieved from memory. We demonstrate the model properties using numerical simulation. Individual travelers are represented as agents, each with their aspirations, which in combination with evaluation results determine whether an agent will start exploring or persist in habitual behavior. The results offer new insights into the evolution of short and long-term dynamics in activity-travel behavior.

Keywords

dynamic behavior, habit formation, choice-set formation, stress, numerical simulation
1 Introduction

Modeling dynamics in activity-travel behavior constitutes the next challenge on the international research agenda. Dynamic models are more valid and sensitive to a larger spectrum of policies. In Miller (2005), it is explained that the key difference between short-term and long-term dynamics is that the former occurs within a context of specific resources and restrictions (e.g. residential or work location, current number of household cars), 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? Should I change my available resources today?) are mutually affected. Specifically, long-term 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, which may trigger long-term changes (bottom-up process).

Prior research on dynamics of activity-travel behavior has predominantly focused either on the top-down process (e.g. tracing the impact of a long-term decision on daily activity-travel patterns) (Salomon 1983, Scheiner et al 2006, Prillwitz et al 2006 and 2007, Vanhulsel et al 2007a, b), or on one time-horizon (e.g. long-term) (Verhoeven et al 2005, Beige et al 2006, Waerden et al 2003a, b, Klokner 2004, Arentze et al 2007b). In contrast, this 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 patterns (Psarra et al 2012a, b, c). The model presented in this paper predicts not only the short-term changes, but also when somebody considers conducting a long-term change, due to dissatisfaction with the daily activity-travel practice. To reach that goal, cognitive and affective responses in spatial choice and learning behavior are simulated, based on principles of reinforcement learning and Bayesian perception updating.

Han et al’s work (2008) on dynamic formation of choice-sets constitutes a basic underpinning of this study. Their work mainly concerns shopping activity type and focuses on location choice-sets. In the current study, this work is extended by taking into account (i) all the activity types that may be included in an individual’s agenda, (ii) not only location, but most of the activity attributes that are considered when making a choice and (iii) the evolution of long-term dynamics.

In the following, first, there will be a description of the conceptual framework of the model, as well as a mathematical interpretation of it. Then, an illustration of the properties of the model, using numerical simulations, follows. Finally, there are conclusions and discussion on future work.

2 THE MODEL

2.1 Repertoire, Scripts and Choice-Sets Normal text

It is assumed that the activity repertoire of an individual is given by a list of i scripts $A_i = \{A_1, A_2, A_3, ..., A_N\}$. The repertoire specifies the type of activities that an individual optionally can perform, as well as the corresponding activity attributes. A script contains information regarding the activity type, the location, the start-time, the origin location and the
transport mode (Arentze et al., 2007a). It is, therefore, a group of decisions, describing a possible way that somebody can travel in order to reach the location of an activity. For instance, two scripts, belonging to the activity list of an individual can be:

\( A_1: \) Shopping, city centre, start time: 10:00, starting from home, bike
\( A_2: \) Shopping, supermarket, start time: 17:30, starting from work, walking

A repertoire is the exhaustive list of all the possible combinations of activity facets that are available to an individual. Thus, it can be regarded as the universal set of all feasible choice combinations that are available to an individual in a specific spatial setting. Undoubtedly, an individual cannot be aware of and consider all these scripts before making a choice at time \( t \). Only a subset of these options is taken into account, which is the choice–set of the individual at time \( t \), for a specific activity type \( k \). A choice-set is dynamic, as new scripts can be explored and added in the choice-set, while others may be discarded, due to memory capacity limitations.

### 2.2 Cognitive and Emotional Values of Scripts

The expected utility of a script \( i_k \), of activity type \( k \), equals:

\[
EU_{i_k}^t = EU_{i_k}^{static} + EU_{i_k}^{dynamic,t}
\]

\[
EU_{i_k}^{static} = \sum_j \sum_n \beta_{jn}^{static} X_j I_{i,j}(x_{jn})
\]

\[
EU_{i_k}^{dynamic,t} = \sum_j \sum_n \beta_{jn}^{dynamic} X_j P_{i,j}^t(x_{jn} | c_t)
\]

where \( EU_{i_k}^{static} \) is the expected partial utility of script \( i_k \) for static activity attributes \( j \) under state \( n \),

\( X_j^{static} = \{x_{j1}, x_{j2}, \ldots, x_{jN}\} \) are the static activity attributes,

\( \beta_{jn} \) is the individual’s preference regarding state \( n \) of activity attribute \( j \).

\( I_{i,j}(x_{jn}) \) equals to 1 if state \( n \) of the activity attribute \( j \) is included in the script \( i_k \), otherwise equals to 0.

\( EU_{i_k}^{dynamic,t} \) is the expected partial utility of \( i_k \), for dynamic attributes under states \( x_{jn} \), \( X_j^{dynamic} \) are the dynamic activity attributes,

\( P_{i,j}^t(x_{jn} | c_t) \) is the conditional, probability distribution across states of \( X_j^{dynamic} \) at time \( t \).

Individuals update beliefs \( P_{i,j}^t(x_{jn} | c_t) \) using Bayesian principles and decision tree induction method (Arentze et al., 2003).

\( c \) stands for context-condition variables (e.g. rush/non-rush hour).

c The actual experienced utility of a script \( i \) at time \( t \) is:

\[
AUT_{i_k}^t = \sum_j \sum_n \beta_{jn}^{static} x_{jn} I'(x_{jn}) + \varepsilon_{i_k}^t
\]

where \( I'(x_{jn}) \) equals 1, if state \( n \) of facet \( j \) was experienced, otherwise equals to 0.

\( \varepsilon_{i_k}^t \) is the surprise experienced at time \( t \).
If there is a difference between the expected and the experienced utility, negative or positive emotions of this experience emerge. The emotional value of an experience event of script $i_k$ is:

$$R'_k = AUT'_k - EU'_{ik}$$  \hspace{1cm} (5)

If the script was experienced several times, the emotional values of the experiences will result in an overall affective value of the script. The emotional value of script $i_k$ at time $t$ equals:

$$E'_k(c) = \begin{cases} 
(1-a_1)E'^{-1}_k(c) + a_1R'^{-1}_k & \text{if } I'^{-1}_k = 1 \text{ and } I'^{-1}_c = 1 \\
(1-a_2)E'^{-1}_k(c) & \text{otherwise}
\end{cases}$$  \hspace{1cm} (6)

where $0 \leq a_1, a_2 \leq 1$ is the trade-off between accumulated past emotional values and the recent ones.

This emotional value plays a role in an overall expected utility of a script $i_k$ at time $t$, as follows:

$$EUE'_k(c) = (1-a_1)EU'_k + a_2E'_k(c)$$  \hspace{1cm} (7)

where $0 \leq a_2 \leq 1$ is a trade-off between rational behavior and affective behavior (based on emotional value).

The updated awareness level of script $i_k$ (awareness level is contingent on event memory of the script) is:

$$S'_k(c) = \begin{cases} 
\max(\lambda S'^{-1}_k(c), R'^{-1}_k) & \text{if } I'^{-1}_k = 1 \text{ and } I'^{-1}_c = 1 \\
\lambda S'^{-1}_k(c) & \text{otherwise}
\end{cases}$$  \hspace{1cm} (8)

where $0 \leq \lambda \leq 1$ is the awareness retention rate.

$I'^{-1}_k$ equals to 1 if the script $i$ was implemented at time $t-1$, otherwise equals to 0.

$I'^{-1}_c$ equals to 1 if the context $c$ was experienced at time $t-1$, otherwise equals to 0.

Therefore, the stronger the emotional impact of the event experience, the longer it stays in memory. Choice-sets are context-dependent and dynamic and consist of those scripts whose awareness level exceeds a threshold, reflecting limited human memory retrieval. The choice-set for activity type $k$ is:

$$\Phi'_k(c) = \{i_k(c) \mid S'_k(c) \geq \omega\}$$  \hspace{1cm} (9)

where $\omega$ is the minimum awareness level for event memory retrieval ability.

### 2.3 Short and Long-term dynamics in Activity-Travel Behavior

Simon (1957) regarded economic man as a satisficing animal, whose problem solving is based on search activity to meet certain aspiration levels, rather than as a maximizing animal. In the proposed model, 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 (house and work location, number of cars, etc) be denoted as $h$. Then, we define $U'_k(c) \mid h$, as the conditional (taking into account these long-term decisions) aspiration
level of activity type \(k\) in terms of the utility level to be attained, under context \(c\). Accordingly, \(U^*_k(c)\) is the unconditional aspiration value of activity type \(k\), under context \(c\), as it is not affected by the restrictions stemming from the long-term decisions. In the current study, stress is defined as the discrepancy between the overall expected utility \(EUE_k^t(c)\) of a script and the conditional aspiration value \(U^*_k(c)\) of this activity.

Nevertheless, people often are unable to keep themselves at their utility-maximizing state and they tend to stick to their habitual behavior. Stress threshold \((\sigma_t)\) is an individual specific parameter, reflecting inertia in an individual’s behavior. Accordingly, in this model, an individual is assumed to always first consider the habitual option, which means the script with the highest activation level in the choice-set (that is most easily retrieved from memory). The updated activation level of script \(i_k(c)\in\Phi_k^t(c)\), at time \(t\) is:

\[
W'_k(c) = \begin{cases} 
\log(W_{i_k}^{t-1}(c)+1) & \text{if } t_{i_k}^{t-1}=1 \text{ and } t_{i_k}^{t-1}=1 \\
\log((\lambda_2 W_{i_k}^{t-1}(c))+1) & \text{otherwise}
\end{cases}
\]

where \(\gamma > 1\) is the recency weight and \(0 \leq \lambda_2 \leq 1\) is the retention rate.

The outcome of the comparison between aspiration and expected utility, given current beliefs, determines whether a habitual or a conscious choice will be made. Habitual behavior is continued if stress is below a threshold, that is, if:

\[
U^*_k(c)\mid h - EUE_k^t(c) < \sigma_t \tag{11}
\]

However, if this difference exceeds the stress threshold, the script with the highest overall expected utility \((i_k^{**}(c)\in\Phi_k^t\) with argmax \(EUE_k^t\)) will be considered. This process of re-considering all available alternatives is called exploitation. Finally, if even this alternative is dissatisfactory, an individual will start exploring new alternatives. The probability of exploring a new script, under context-condition \(c\), is:

\[
P'(i_k(c)\mid J') = \frac{\exp(V_k(J'\mid c) / \tau)}{\sum_j \exp(V_k(J'\mid c) / \tau)} \tag{12}
\]

where \(\tau\) is the degree of information lack in the study area,

\[
J' = \{ j \mid U_{i_k(j)}^t(c)\mid h - eu_{i_k(j)}^t(c) > \sigma_j \} \forall j \tag{13}
\]

are the dissatisfactory activity facets of \(i_k^{**}(c)\in\Phi_k^t\) and

\[
V_k(J'\mid c) = \sum_{j\in J'} eu_{i_k(j)}(c) \tag{14}
\]

is the utility measure of each script of activity type \(k\), not belonging to the choice-set. This utility measure is based on the expected utility of the facets causing dissatisfaction at time \(t\) and under condition \(c\).

It is assumed that an individual will keep a record \((N_k^{t-1})\) of how many consecutive times (s)he conducted an exploration for an activity type, under the same context. As the exploration effort is built up, instead of continuing exploring, the individual will avoid further frustration by lowering the aspiration level of the activity facets that caused dissatisfaction. 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:
\[ P\left( \text{lowering} U^*_h(c) \mid h \right) = \frac{\exp(\mu + \nu(N'_k - N_0))}{1 + \exp(\mu + \nu(N'_k - N_0))} \]  

(15)

where \( \mu, \nu \) and \( N_0 \) are parameters of the logistic function. When lowering \( U^*_h(c) \mid h \), the individual replaces the current conditional aspiration level of the dissatisfactory activity facets with the corresponding activity facet’s aspiration level of the script that currently has the highest expected utility.

Adaptations can be either short-term changes within a given set of opportunities (e.g. changing route) or long-term changes in the available resources (e.g. purchasing a car). This model predicts when an individual gets “awake” and considers conducting a long-run adaptation. This point constitutes the boundary of this study, which aims at linking short and long-term dynamics of activity travel behavior.

The conditional and unconditional aspiration values of an activity type \( k \) (\( U^*_k \mid \text{h} \) and \( U^*_k \)) can be calculated by weighting across all context-conditions \( c \). The actually experienced utility of the current long-term decisions can be calculated by adding the conditional aspiration values of the \( k \) activities:

\[ U_h = \sum_k U^*_k \mid \text{h} \]  

(16)

This is because the conditional aspiration values are defined in the context of the constraints that the current long-run decisions impose. On the other hand, the expectations of an individual, regarding his/her context of long-term decisions, can be estimated by adding the unconditional aspiration values of the activity types. Therefore, the aspiration value for long-term decisions is:

\[ U^*_r = \sum_k U^*_k \]  

(17)

Let \( \sigma_2 \) be the stress threshold for the long-term level. We assume that if:

\[ U^*_r - U_h < \sigma_2 \]  

(18)

the individual does not consider making a long-term change, as he does not suffer by stress on this long-term level. Otherwise, the individual becomes “awake” and considers conducting a long-term adaptation.
Figure 1: Flow diagram of the model

Figure 2: Sub-flowchart, focusing on the process of selecting a script
3 Numerical Simulation

3.1 Simulation Settings

To examine the behavior of the model, a series of numerical simulations was conducted. These simulations focus on work, shopping and leisure activities. The model starts with the five agents not being aware at all of the area. Every time that an activity needs to be conducted, each agent implements a script. Based on this experience, the agents update the emotional value, the awareness and activation level of the selected script. On the other hand, the same indicators of the non-selected scripts are lowered, based on a forgetting process (figures 1, 2, 3). When an agent becomes ‘awake’ (considers conducting a long-term change), it stops acting (figure 1). The residential and work locations of the 5 agents were arbitrarily selected. Moreover, a supermarket close to their neighborhood, a social club and a friends’ home location correspond to each agent (figure 4). The schedule of the three activities is predefined and the same for all the agents. There are four context-conditions (weekday/weekend, rush/non-rush-hour). A Monte Carlo simulation determines which condition is experienced by an agent, at time t. Due to simplification, travel cost is regarded as static, while travel time as dynamic. Specifically, three levels of delay are assumed (low, medium and high) and for those scripts where the transport mode is carpooling or bus, they correspond to three travel times (relevant to each level of delay). (table 1)
Figure 4: The spatial setting of the simulation

![Spatial Setting](image)

Table 1: The activity list that is used as an input file of the simulation

<table>
<thead>
<tr>
<th>$i$</th>
<th>$i_k$</th>
<th>$k$ (activity)</th>
<th>location</th>
<th>transport mode</th>
<th>origin</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1_work</td>
<td>Work</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>1_work</td>
<td>Work</td>
<td>bike</td>
<td>from home</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>1_work</td>
<td>Work</td>
<td>carpooling</td>
<td>from home</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>1_work</td>
<td>Work</td>
<td>bus</td>
<td>from home</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>2_shopping</td>
<td>super market</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>6</td>
<td>2</td>
<td>2_shopping</td>
<td>super market</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>2_shopping</td>
<td>city center</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>2_shopping</td>
<td>city center</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>9</td>
<td>5</td>
<td>2_shopping</td>
<td>super market</td>
<td>bike</td>
<td>from home</td>
</tr>
<tr>
<td>10</td>
<td>6</td>
<td>2_shopping</td>
<td>super market</td>
<td>bike</td>
<td>from work</td>
</tr>
<tr>
<td>11</td>
<td>7</td>
<td>2_shopping</td>
<td>city center</td>
<td>bike</td>
<td>from home</td>
</tr>
<tr>
<td>12</td>
<td>8</td>
<td>2_shopping</td>
<td>city center</td>
<td>bike</td>
<td>from work</td>
</tr>
<tr>
<td>13</td>
<td>9</td>
<td>2_shopping</td>
<td>super market</td>
<td>bus</td>
<td>from home</td>
</tr>
<tr>
<td>14</td>
<td>10</td>
<td>2_shopping</td>
<td>super market</td>
<td>bus</td>
<td>from work</td>
</tr>
<tr>
<td>15</td>
<td>11</td>
<td>2_shopping</td>
<td>city center</td>
<td>bus</td>
<td>from home</td>
</tr>
<tr>
<td>16</td>
<td>12</td>
<td>2_shopping</td>
<td>city center</td>
<td>bus</td>
<td>from work</td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>3_leisure</td>
<td>Sportclub</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>18</td>
<td>2</td>
<td>3_leisure</td>
<td>Sportclub</td>
<td>walk</td>
<td>from work</td>
</tr>
<tr>
<td>19</td>
<td>3</td>
<td>3_leisure</td>
<td>visiting friends</td>
<td>walk</td>
<td>from home</td>
</tr>
<tr>
<td>20</td>
<td>4</td>
<td>3_leisure</td>
<td>visiting friends</td>
<td>walk</td>
<td>from work</td>
</tr>
<tr>
<td>21</td>
<td>5</td>
<td>3_leisure</td>
<td>Sportclub</td>
<td>bike</td>
<td>from home</td>
</tr>
<tr>
<td>22</td>
<td>6</td>
<td>3_leisure</td>
<td>Sportclub</td>
<td>bike</td>
<td>from work</td>
</tr>
<tr>
<td>23</td>
<td>7</td>
<td>3_leisure</td>
<td>visiting friends</td>
<td>bike</td>
<td>from home</td>
</tr>
<tr>
<td>24</td>
<td>8</td>
<td>3_leisure</td>
<td>visiting friends</td>
<td>bike</td>
<td>from work</td>
</tr>
<tr>
<td>25</td>
<td>9</td>
<td>3_leisure</td>
<td>Sportclub</td>
<td>bus</td>
<td>from home</td>
</tr>
<tr>
<td>26</td>
<td>10</td>
<td>3_leisure</td>
<td>Sportclub</td>
<td>bus</td>
<td>from work</td>
</tr>
<tr>
<td>27</td>
<td>11</td>
<td>3_leisure</td>
<td>visiting friends</td>
<td>bus</td>
<td>from home</td>
</tr>
<tr>
<td>28</td>
<td>12</td>
<td>3_leisure</td>
<td>visiting friends</td>
<td>bus</td>
<td>from work</td>
</tr>
</tbody>
</table>

Table 1: The activity list that is used as an input file of the simulation
The surprise term for actual experienced utility is generated using a normal distribution with mean 0 and standard deviation 0.25. For every agent, the basic settings are: 1) awareness threshold $\omega = 0.05$, 2) awareness retention rate $\lambda_1 = 0.99$, 3) parameter for updating activation levels $\gamma = 1.5$, 4) activation level retention rate $\lambda_2 = 0.9$, 5) parameters for calculating the probability of lowering conditional aspiration levels $\mu = 0.1$, $\nu = 1$ and $N_0 = 3$, 6) stress threshold for short-term horizon $\sigma_1 = 8$ and for long-term horizon $\sigma_2 = 16$, 7) uncertainty parameter for exploration $\tau = 1$.

### 3.2 Some Results

In the simulation example, illustrated in this paper, the first agent becomes awake on the 48th day, while the rest four agents manage to develop some habitual behavior within the current context of their long-term decisions. In total, 7000 choice occasions take place, and then the simulation was stopped by the user.

Figures 5a and 5b show the results regarding the average size and the overall expected utility of the choice-set the five agents hold over time for shopping activity, across the four conditions. The size of the choice-set is not fixed, but after some time it tends to stabilize. The waving curves, showing the choice-set size, reflect the dynamics of the choice-sets, which stem from adding newly discovered scripts and discarding ones that were forgotten. It is also interesting to see the big decrease in the overall expected utility of the choice-set that the first agent holds, before it became ‘awake’. This implies that before considering a long-term change, it suffered from increasing stress, as a result of many unsuccessful explorations. Figures 5c and 5d show the results for the four context-conditions regarding the average size and overall expected utility of the choice-set across the agents, for work and leisure activities. The expected utility in the context of non-rush hours is usually higher than the expected utility for rush hours.

Figure 6a depicts the dynamic fluctuation over time of the aspiration values of the first agent. Usually the aspiration values that the agents hold for the activity types are lowered at the beginning of the simulation (to become more realistic) and this results in lowering the actually experienced utility of long-term decisions. This triggers increased feeling of stress, as the deviation between the aspiration for long-term decisions and the actually experienced utility of long-term decisions increases. When the distance between these two values exceeds a threshold the agent becomes ‘awake’.

Finally, a detailed example of a dynamic process of the second agent, with eleven consecutive choices under the same context condition and for the same activity type, is depicted in Figure 6b. The agent starts with an exploration choice (its choice-set was empty). After two consecutive explorations, it manages to find a satisfactory script, which becomes its habitual option. However, as there is a lot of time (42 days) until this agent confronts the same activity type and context again, the awareness level of this habitual script, was lowered and therefore it was discarded from choice-set. Then, six consecutive exploration efforts follow, resulting in an increased feeling of stress and thus in the lowering of agent’s aspirations. After that, the expected utility of the script with the maximum activation level in the choice-set, is within the tolerance range of the agent. Therefore, this script becomes the habitual option. The expected utility of this habitual option is slightly decreasing, due to the non-stationary environment.
Figure 5: Size and overall expected utility of choice-sets (agent and context specific)
Figure 6: Fluctuation of aspirations (1st agent) and characteristic example of 11 consecutive choices

4 Conclusions

This paper outlined the conceptual framework underlying a multi-agent system of dynamic processes of habit formation and dynamic adjustments of activity-travel behavior. Agents learn about the environment, adapt to changing circumstances and improve less effective behavior. Finally, they may also consider conducting a long-term change.

This model constitutes a first step towards a fully operational model of dynamic activity-travel patterns. A case study of three activity types is illustrated in the paper. The emerging patterns of aspirations, frequency and overall expected utility of different choice modes, size and overall expected utility of the choice-sets respond in relatively logical ways.

The next step is to observe how the agents would react after reaching a habitual state, in case that an exogenous change takes place. Furthermore, the framework could be extended to integrate social learning. Additionally, an important extension would be modeling the way that people explore and take long-run decisions, after becoming “awake”. Finally, future research should focus on the analysis of empirical data, which would serve to estimate the parameters and validate this dynamic model. These data could be collected with a stated adaptation experiment (Psarra et al, 2013).

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