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**Modelling Context-Sensitive Dynamic Activity-Travel Behavior Under Conditions of
Uncertainty Incorporating Reinforcement Learning, Habit Formation, And
Behavioral and Cognitive Adaptation Strategies**

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Abstract:

This paper develops a framework for modelling the dynamic formation of location choice-sets. The proposed framework integrates three key concepts, namely aspiration, activation and expected utility. Aspirations are defined at the level of attributes of choice alternatives and represent an individual's beliefs about performance levels that potentially can be achieved. Activation levels are defined at the level of choice alternatives and represent the ease with which an alternative can be retrieved from memory and, hence, the degree of awareness of an alternative. Finally, expected utility represents an individual's evaluation of a choice alternative based on his/her current beliefs about attributes of the alternative. In the proposed system, all these cognitions - aspirations, activations and beliefs - are conditional upon context variables and subject to cognitive and social learning under uncertainty. We describe the core of the model and illustrate its properties using numerical simulation.

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probably needs updating

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Word count: $5987 + 6 \cdot 250 = 7497$

1 Introduction

Recently, activity-based analysis has slowly shifted gear from analysis of daily activity patterns to analysis and modelling of dynamic activity-travel patterns. Dynamics have been examined from different time horizons. For example, Waerden, Borgers and Timmermans (2003a, 2003b) and Klökner (2004) argued that people may reconsider their typical behaviour in response to long-term key lifecycle events and that these may therefore be relevant concepts for studying the dynamics of activity-travel patterns. Example of such studies of the effect of lifecycle events on travel patterns include (Verhoeven, *et al.*, 2005, Beige and Axhausen (2006), Prillwitz and Lanzendorf (2006, 2007), and Vanhunsel, *et al.* (2007). Other studies have examined the impact of annual events such as Christmas on activity-travel patterns (Arentze and Timmermans, 2006, 2007). Yet other studies have explored day-to-day variability in activity-travel patterns. Finally, research on adaptations of activity-travel schedules due to unexpected events is slowly expanding (Timmermans, *et al.*, 2001; Joh, *et al.* (2006), Nijland, *et al.* (2006, 2007) and Roorda and Andre (2007). A more detailed and complete review of this work is given in Arentze and Timmermans (2007).

As suggested by this brief review, these attempts use different methodologies and concepts. There is hardly any evidence of an integrated conceptual framework and especially of a consistent associated set of modeling tools that could function as the building blocks for the development of dynamic models of activity-travel patterns. Most existing work seems to focus around TASHA and MATSIM. Miller (2005) formulated an integrated framework for modelling short run and long run dynamics. It includes some useful ideas, but modelling work on its components has just started. For example, Nurul Habib and Miller (2006, 2007) suggested a model for dynamic activity generation. They assumed that the utility of an activity is divided into two parts: the goal utility and the process utility. The goal utility is gained by the end state accomplished by the activity and the process utility is gained by the execution process of the activity. The goal utility component represents the direct utility of the activity episodes and defines the activity program generation stage. The process utility is a feature of the activity act itself and will generally depend upon duration, which in turn will depend on activity scheduling and rescheduling trade-offs for different candidate activities drawn from the activity-agenda. They assume that the total utility of the activity program consists of the utility derived from all activities under consideration and the utility derived from all other activities, modelled as a composite activity. Another highly interesting set of papers is concerned with the development of MATSIM-T, a multi-agent environment for travel simulation (Balmer *et al.*, 2006). Part of this system concerns a *replanning module* that is activated when agents modify daily their plan. Agents have a utility function that is defined as the sum of individual utilities of each activity present in the plan. It is a function of the duration of the activity, travel costs and penalties for coming late, leaving too early, etc. (Charypar and Nagel, 2005). At first, a dedicated genetic algorithm (Meister, *et al.*, 2005, 2006) was developed for generating the schedules, later a covariance matrix evolution strategy was used (Charypar *et al.*, 2006). Agents select certain plans probabilistically. Simple learning rules are used to dynamically update the suitability/utility of daily schedules. To date it seems that the focus has primarily been on the development of the software environment in the sense that some operational models are still quite removed from the author's ambitions.

In this paper we describe and illustrate the framework that is developed in the contexts of the FEATHERS project (Arentze, *et al.*, 2006; Janssens, *et al.*, 2006), coordinated by IMOB, University of Hasselt, jointly with other universities and research institutes. Part of the project is concerned with developing a dynamic activity-based model, jointly with the Urban

Planning Group of the Eindhoven University of Technology. It will integrate and elaborate some earlier research of the latter group and explore some new concepts where relevant. As we will discuss in more detail below, the framework underlying the multi-agent system allows simulating habit formation and adaptation. It predicts habitual behaviour versus exploitation and exploration as a function of discrepancies between dynamic, context-dependent aspiration levels and context-dependent expected utilities. Principles of mental effort and memory traces are used in simulating different types of behaviour, taking uncertainty, generated endogenously, into account.

In the remainder of this paper, we will describe the core of the conceptual framework underlying the model and illustrate its properties using numerical simulations. It should be stated from the outset that the actual multi-agent system is more elaborate than can be discussed in this paper due to page limitations. Especially, we will not discuss the simulation of the social network and related information exchange, adaptations of mutual choice sets and formation of common aspiration levels that constitutes another component of the multi-agent system. We will start by describe the components of the system along with how it work together as a whole. This will be followed by introducing an illustration case study. Finally, a conclusion and discussion for future research will complete the paper.

2 The model

In the context of transportation planning, we typically address problems of individual decision making in a spatial setting, described by located facilities and a transportation system, sometimes mediated through an institutional framework. Let $L_i(X_j)$ denote the set of attributes that describes a particular choice alternative. It normally will consists of a subset of attributes that are or for purpose of analysis can be viewed as temporally invariant, and a set of dynamic attributes that are inherently non-stationary in the sense that it describes the combined behaviour of the individuals. An example would be crowdedness.

Opmerking [H.J.P.2]: Introduce symbols

Opmerking [H.J.P.3]: likewise

Individuals do not make decisions on the actual attributes of these choice alternatives, but rather on their perfection of beliefs about these attributes. Perception is not necessarily perfect. In fact, individuals will have imperfect and incomplete information about the choice alternatives in their environment and their attributes. In the short run, these perceptions of beliefs about the stationary attributes will be constant context-independent, ignoring learning for now. However, individuals will build up context-dependent beliefs about the non-stationary attributes. These attributes are fundamentally uncertain and hence each of these attributes may be in a certain state. We assume that for each dynamic attribute, X_j , the individual uses some classification, denoted as $X_j = \{x_{j1}, x_{j2}, \dots, x_{jN}\}$, where $x_{j1}-x_{jN}$ represent possible states of X_j , and specifies his/her beliefs regarding location i based on his/her current knowledge as a probability distribution across X_j denoted as $P_i(X_j)$, which sums up to 1. The degree of uncertainty is given by the degree of uniformity of $P_i(X_j)$. The more evenly the probabilities are spread across possible states, the larger the uncertainty and vice versa. As indicated, state probabilities are conditional upon certain contextual variables. For example, crowdedness of a shopping location will depend on day-of-the-week and time-of-the-day. Let these conditional time-varying probabilities be denoted by $P^t(X_j|C)$, where C stands for one or more condition variables. The expected utility of a choice alternative given a set of beliefs about the attributes of the location (including travel time) is then equal to

$$EU_i^t(c_k) = EU_i^{static} + EU_i^{dynamic}(c_k) \quad (1)$$

$$EU_i^{static} = \beta X_j \quad (2)$$

$$EU_i^{dynamic}(c_k) = \sum_j \sum_n \beta_j x_{jn} P_{ij}^t(x_{jn}|c_k) \quad (3)$$

where EU_i^t is the expected utility of choice alternative i at time t , β_j is the expected partial utility of location i for static attributes j and $\beta_j x_{jn} P_{ij}^t(x_{jn}|c_k)$ is the expected partial utility of location i under possible states x_{jn} with probabilities $P_{ij}^t(x_{jn}|c_k)$ and preference β_j regarding dynamic attribute j . $c_k = (c_{1k}, c_{2k}, \dots, c_{lk})$ represents the values of the relevant condition variables under the k -th condition.

Beliefs about attributes and awareness of choice alternatives in the environment are not stable, but rather dynamically change over time as individuals learn about their environment in multiple ways, including social interaction, communication media and by implementing their activity-travel patterns. Given limited available space for this paper, we will focus here on the latter. By implementing activities, individuals visit particular destinations and experience attributes, thereby reinforcing their beliefs and updating their memory trace regarding their awareness of alternative destination in their environment. Thus, each time a location is chosen when an activity is implemented, the individual updates beliefs $P^t(X_j|C)$. First, this process involves incrementally updating the conditional belief distributions across the possible states for each observed attribute of the choice alternative after experiencing the actual states. Second, it involves periodically reconsidering whether the set of condition states that are mentally used to discriminate between states of attributes is still adequate or that this mental representation of states should be updated.

Operationally, this notion is implemented as suggested in Arentze and Timmermans (2003), using Bayesian principles and decision tree induction method. Dynamics in the level of awareness of choice alternatives, called activation level here, are contingent on the utility of the alternative. Following Anderson (1983), the basic assumption is that an alternative that has higher utility stays longer in memory, and that memory is reinforced when an alternative is chosen and memory decays if it is not chosen. Every time an alternative is chosen, its activation level is incrementally increased and its memory trace is strengthening. The reinforcement rate is an increasing function of the experienced utility of the chosen alternative. Because individuals have a limited memory retention capacity, the memory trace will decay over time. If an alternative has not been chosen for some time, its activation level will decrease. When its activation level drops below some predefined threshold, the alternative will be removed from the individual's choice-set, reflecting limited human ability of memory retrieval. Formally, let q be the number of relevant condition variables, $W_i^t(z_m)$ be the activation level of an alternative i under condition m , where $z_m = (z_{1m}, z_{2m}, \dots, z_{qm})$ represents the states of the q condition variables under condition m , and ω be a minimum activation level for memory retrieval ability. The strength of a memory trace or activation level of a particular alternative i in the choice-set then equals:

$$W_i^{t+1}(z_m) = \begin{cases} W_i^t(z_m) + \gamma U_i^t(z_m) & \text{if } I_i^t = 1 \\ \lambda W_i^t(z_m) & \text{otherwise} \end{cases} \quad (4)$$

where $I_i^t = 1$, if the alternative was chosen at time t , and $I_i^t = 0$, otherwise, $0 \leq \gamma \leq 1$ is a parameter representing a recency weight, which is relevant only when the alternative is chosen; and $0 \leq \lambda \leq 1$ is a parameter representing the retention rate. $U_i^t(z_m)$ is the experienced utility attributed to alternative i that is calculated based on experienced states of

the attributes of alternative i , including both (quasi)-static and dynamic variables. At every time t , a choice set will consist of those alternatives which activation level exceeds a threshold:

$$\Phi^t(z_m) = \{L_i | W_i^t(z_m) \geq \omega\} \quad (5)$$

Opmerking [H.J.P.4]: We have concept awareness, activation level, memory trace- shouldn't we use one of these and consistently use that one???? Use activation level

Thus at every moment in time when individuals have to choose a particular alternative, they hold a set of context-dependent beliefs about the state of the alternatives in their choice set, which includes a subset of actual choice alternatives in their environment with a differentiating context-dependent activation level. Table 1 shows an example of an activation level pattern for shopping locations.

Making a decision require mental effort, depending on the degree of involvement in the decision process, which in turn will also be context-dependent. As implied by the definition of activation level, the alternative that has the highest activation level in the choice-set is the one that is most easily retrieved from memory and thus requires least mental effort. We assume that if this alternative is acceptable, individuals will choose that alternative with the highest activation level, which represent the case of habitual behaviour. Acceptance depends on an individuals' aspiration level, which is defined both at the level of choice alternatives and the level of individual attributes. Attribute-specific aspiration levels give direction to exploration processes (e.g., find alternative stores with a lower price level rather than find stores that have higher utility for my purposes) and serves as a subjective reference point, which determines what qualifies as a satisfactory outcome for that attribute. Aspiration levels are dynamic and context-specific. We denote the set of current aspiration values as $A = \{A_k\}$, where $A_k = (c_k, e_k)$, $e_k = (e_{1k}, e_{2k}, \dots, e_{jk})$, e_{1k} represents the aspiration value of the first attribute under the k -th condition, and $c_k = (c_{1k}, c_{2k}, \dots, c_{jk})$ defines the k -th condition as a set of states of the condition variables considered.

The outcome of a comparison between aspiration and expected outcome given current beliefs determines whether an individual will continue his habitual behaviour or will explore and choose other alternatives. It marks a switch from habitual behaviour to a conscious choice mode. We assume that if dissatisfaction (i.e., the difference between aspiration and expected outcome) regarding at least one attribute exceeds the tolerance threshold, an individual will switch to another mode of behaviour and start searching consciously for better alternatives. This tolerance threshold is a predefined and individual specific parameter that reflects a characteristic of the individual. A large tolerance threshold indicates the individual strongly dislikes the mental effort involved to make better actions and is easier satisfied with the current situation. Vice versa, a small threshold implies that an individual sets higher standards in what is found acceptable or has a higher propensity to explore. Formally, habitual choice is:

$$\{L_i(\max W_i^t(z_m)) | X_j(c_k) - e_j(c_k) \leq \varepsilon_j \forall j\} \quad (6)$$

We assume that when acting in a conscious mode, individuals will first be engaged in exploitation in the sense that they will search in their choice-set for a better alternative. An individual is assumed to choose the alternative with the highest expected utility which does not violate the tolerance threshold for any attribute, relevant for the decision. Formally, exploitation choice is:

$$\{L_i(\max EU_i^t(z_m)) | X_j(c_k) - e_j(c_k) \leq \varepsilon_j \forall j\} \quad (7)$$

If for at least one attribute of the alternative with the highest expected utility in the current choice set exceeds the tolerance thresholds, the individual will start and explore new

alternatives beyond his current choice set. This process of exploration as opposed to the process of exploitation, is not random, but rather goal-directed in the sense that the exploration process will be guided by the attribute(s) that caused dissatisfaction. However, we have assumed that choice sets are experience-based. Individuals may hear of new alternative through word-of-mouth of members of their social network. This is modelled separately but this part of beyond the scope of the present paper. In addition, they may be passively exposed to advertisement or other information attracting the attention to new choice alternatives, or they be actively searching for information. We assume that the probability of exploring a new alternative is proportional to the utility of that alternative based on the attributes that are not satisfied by the alternatives within the current choice-set. It reflects the notion that the marketing of choice alternatives will reflect its unique features. Because these alternatives are unknown to the individuals, they are inherently uncertain. The degree of uncertainty may however vary from choice situation to choice situation and therefore, we include a parameter in this model predicting the probability of exploring a new alternative, specified as:

$$P(L_i^t) = \frac{\exp(V_i^t / \tau)}{\sum_i \exp(V_i^t / \tau)} \quad (8)$$

$$V_i^t = EU_i^t(c_k, X_j) \quad \text{where} \{j | X_j(c_k) - e_j(c_k) > \varepsilon_j\} \forall j \quad (9)$$

where V_i^t is the utility measure of alternative i concerning the dissatisfied attributes j and τ is a parameter reflecting the degree of uncertainty in the selection of new locations. The larger the value of τ , the more evenly probabilities are distributed across alternatives and, hence, the higher the uncertainty. V_i^t is a utility calculated based on true levels of dissatisfactory attributes of the choice alternatives. Furthermore, a disutility of travel distance is included in V_i^t to acknowledge that the longer the travel distance, the less likely information about the location is available and, the longer the travel distance is, the less likely the location will be considered by the individual because of the higher generalized travel costs.

In addition, a mental effort counter is included to prevent an individual from getting trapped in continuous and endless exploration. We assume that individuals will keep some record of how many consecutive times they already tried exploring a new location under the same contextual conditions. Every time a choice is made through exploration, it will add 1 unit of mental effort. A habitual choice or an exploitation choice will break the chain of incrementing the score and restore it back to 0. We assume that when the mental effort involved in search for a better alternative is built up and exceeds a predefined threshold, instead of continuing exploring, the individual will avoid further frustration by lowering the aspiration level (realising that the current aspiration level is not realistic). Therefore, in the choice process, before engaging in exploration, the system will check whether the accumulated mental effort exceeds this threshold. If this threshold is not exceeded, the individual will continue exploring. When it is exceeded, the individual will replace the current aspiration levels with the attributes levels of the alternative that currently has the highest expected utility to assure a relatively optimal outcome and maintain high aspiration levels for future choices. As a consequence of choosing it, the activation level of this alternative will be increased.

As a consequence of the above mechanisms, an individual arrives at a selection of a single alternative location each time an activity is to be carried out. Depending on aspiration levels, this alternative could be the one that has the highest activation level (habitual choice), the one that has the highest expected utility (conscious exploitation choice), or the one that

Opmerking [H.J.P.5]: Is this correct and if so why did we conceptualise it like this. Only try the alternative with the highest expected utility, not every alternative in the set.

Opmerking [H.J.P.6]: Is this correct-could it be multiple attributes? Yes, it could be multiple.

Opmerking [H.J.P.7]: Tried to give some reasoning for this choice but see other comments – what happened to inclusion in choice sets as a function of where activities are conducted – is that also included????

Opmerking [H.J.P.8]: If we introduce notation for subset of X not meeting the criteria this could be formalised a bit more strict I try to write. Please check correctness.

Opmerking [H.J.P.9]: Why don't we generalize this and make to location or location type specific, reflecting the notion that my uncertainty may differ based on a priori knowledge

Opmerking [H.J.P.10]: BEHAVIORALLY THIS IS A WEAK POINT, BECAUSE OUT INDIVIDUALS HAVE NO CLUE ABOUT THE ATTRIBUTES. I WOULD PREFER TO REPLACE THIS BY SOMETHING LIKE BIGGER BECAUSE MORE CHANCE OF FINDING SOMETHING AND DISTANCE AS IT INVOLVES LESS EFFORT, PLUS COMMENT 7.

Opmerking [H.J.P.11]: Again, we did not yet incorporate this

Opmerking [H.J.P.12]: Not clear whether this applies to searching in general or to a particular new alternative, avoiding exploring it over and over again. It is in general.

was newly discovered (conscious exploration choice). Figure 1 schematically shows the main step of the decision making process by which the model arrives at a choice.

3 Illustration

The framework developed above is rich in behaviour and as a consequence too complex to allow examining the behaviour of the model without first trying with numerical simulation. To reveal the separate impacts of the various components of dynamics, a series of scenarios should be set up starting with basic conditions and incrementally adding complexity. Due to space limitations, this section focuses on a first series of the large set of simulations. The simulations discussed here focus on one activity – shopping, and test the separate effects of the components: 1) mental effort limit (willingness to spend effort), 2) activation level threshold (memory space), and 3) self aspiration threshold.

Settings

The simulation considers an area of 100 by 100 cells with 100 meter by 100 meter each. There are 12 shopping locations including 6 small, 4 medium and 2 big shopping centres. The locations of these shopping centres are predefined across the study area. There are 6 agents with their residential location and work location respectively. These locations are also the origins of the agent for a shopping trip. The input schedule for the 6 agents is arbitrary generated with only one shopping activity a day for 72 days in total. The frequency of the shopping activity is scheduled as equal as possible in any of the four context conditions (weekday vs. weekend and rush hour vs. non-rush hour) as well as the origin (from home or from work). Six static attributes of the shopping centre are included: 1) the size of the shopping centre (big, medium, or small), 2) store for the daily goods present (yes or no), 3) store for semi-durable goods present (yes or no), 4) store for durable goods present (yes or no), 5) price level (high, middle or low), and parking space (yes or no). These attributes define the characteristics of each shopping centre. Only one dynamic attribute – crowdedness is included with four states as {No, Little, Medium, Very}. Travel time is calculated by physical distance at this stage. The initial knowledge of each agent is based on a pre-study outcome using the same model starting with not knowing any of the locations and the highest aspiration level for each agent for every attribute.

The process

The results reported here are the average results across 100 simulation runs. A simulation run considers a time period of 72 days. On each day, each agent considers choosing a location for its shopping activity. Dependent on its schedule, the agent checks out the alternatives in its context dependent choice-set. Note that the choice set with the context condition of departure from home might be different from the choice set with the context condition of departure from work. The same applies to the rest of context conditions used to define the activation level. Based on its aspiration level of the day, the agent goes through a decision process as described in the model section to arrive at a choice. Before going to the next day, the agent updates its knowledge, in particular, activation level and beliefs about the state of the environment. For the results reported in this paper, the structure learning part is left out of consideration. Only the parameter learning is considered. For every agent, the basic setting is: 1) the activation threshold $\omega = 0.03$, 2) the parameter for updating activation levels $\gamma = 0.99$ and $\lambda = 0.2$, 3) the self aspiration threshold $\varepsilon = 1$ and the uncertainty parameter $\tau = 1$.

Some results

Figures 2a, 2b and 2c show the general results of the basic case both considering context and agent. As expected, the expected utility of the choice set slightly increases across the 72 days. The expected utility in the context of non-rush hours is higher than the expected utility for rush hours. Across the 72 days, each agent's expected utility of the choice set also slightly increases as a result of learning. The size of the choice set is not fixed, but shows a tendency to first decrease and then to increase across contexts and agents. The range in the size is reasonable with an average around 1.4 for each context and each agent. The waving curve showing the renewal rate explores the dynamics of the choice sets as the newly discovered alternative enters the choice set, and the ones not choosing for a long time are discarded.

Figures 3a, 3b and 3c show impacts of mental effort on choice mode frequency, expected utility of different choice modes, the size of the choice set and the renewal rate of the choice set respectively. In line with one's expectation that higher mental effort indicates a higher willingness to spend effort to explore, Figure 3a depicts the frequency of exploration behaviour as an increasing function of mental effort. As the exploration behaviour increases, habitual behaviour decreases. Also because more exploration increases the possibility to discover a new alternative that may satisfy the aspiration level, the frequency of lowering aspiration levels declines slightly. As one could expect, more exploration also increases the possibility of discovering a new alternative that is not that good, which will reduce the average expected utility of the choice set. Although these imperfect alternatives will not stay that long in the choice set because of activation level updating, they will temporally influence the average expected utility of the choice set as shown in Figure 3b with a slightly declining trend line. As it turned out, the expected utility of habitual choices is not always the highest among all the choice modes; the expected utility of exploitation choices is more often the highest. The expected utility of exploration choices is the lowest because of the uncertainty in discovering an alternative. As Figure 3c shows, increasing mental effort implies more exploration, and therefore the size of the choice set and the renewal rate of the choice set both increase.

Figures 4a, 4b and 4c illustrate the impact of activation level threshold on choice mode frequency, expected utility of different choice modes, size of the choice set and the renewal rate of the choice set respectively. As described in the model section, the activation level threshold indicates an agent's memory space. With a high activation level threshold, an agent needs a strong memory trace to remember the alternative, and is more easily forgetting things or discarding its memory. As it turns out (Figure 4a), when the activation level threshold increases, habitual choices decrease, while exploration choices increase. The pattern of these changes follows a curved line, not a straight line. Thus, the relation between them is not a simple linear function, but more complex. The average expected utility has a slight trend to decrease when the activation level threshold increases. As we would expect (Figure 4b), the expected utility of habitual choices is lower than that of exploitation choices in most of the settings. When the activation level threshold is extremely high, the choice set may not contain any alternative, since none of the alternative meets the requirement. In this case, the agent tends to explore new alternatives every time a choice has to be made. It is shown in Figure 4c. As the activation level threshold increases, the size of the choice set reduces, getting close to 0, while the renewal rate of the choice set increases and approximates 1.

Figures 5a, 5b and 5c illustrate the impact of self aspiration threshold on choice mode frequency, expected utility of different choice modes, size of the choice set and renewal rate of the choice set respectively. As it turns out, when aspiration threshold increases, habitual choices increase, lowering aspiration levels to settle a choice decreases slightly and exploration choices diminishes quickly. It is in line with what we would expect. Since self aspiration threshold is an index of tolerance that is used in judging a satisfactory outcome, a

higher tolerance threshold indicates that an agent is more easily satisfied with current situation. Thus, this is accompanied with a higher possibility of following habit, not investing effort to make better choices. As a consequence, as shown in Figure 4b, the expected utility of habitual choices may decrease with an increasing tolerance threshold. It also brings about the decreasing effect, both in the size and renewal rate of choice sets, as shown in Figure 4, which is different from the previous element effects.

Interpretation

Even under the very basic conditions considered here, the emerging patterns in the behaviour of the multi-agent system are already quite complex. The patterns of choice mode frequency, expected utility of different choice modes, size of the choice sets and renewal rate of the choice sets appear to be unique for these proposed elements of the model even though some of them might have similar impact on one of the respects. As it turns out, the model is capable of distinguishing habitual choice, exploitation choice and exploration choice. It provides a modelling approach for simulating habit formation and adaptation under uncertainty.

4 Conclusion and discussion

This paper has outlined the conceptual framework underlying a multi-agent system that will be used to model the dynamic processes of path-dependent and equilibrium habit formation, adjustment to exogenous and endogenous changes in attributes of choice alternatives and impact of life trajectory events. The basic assumption is that individuals (simulated agents) act based on behavioural principles and mechanisms. They hold beliefs (knowledge) about their environment during a certain life course, which are developed as a function of activity-travel patterns, information exchange in their social network, passive exposure to various communication channels and active search. Individuals have context-dependent preferences and needs, leading to plans, agendas and schedules. They carry out those plans, agendas and schedules in time and space, reinforcing their context-dependent beliefs, memory traces and aspiration levels. Significant discrepancies between expectation and aspiration, due to exogenously changing attributes of the non-stationary environment or transportation system, or endogenous change due to lifecycle trajectories or changing accumulative behaviour of agents, may lead to exploring new alternatives, leading to changing choice sets. Thus, agents learn about the environment and the consequences of their actions, cope with and adapt to changing circumstances and improve less effective behaviour. Based on their experiences, agents form habits, reinforce memory traces, update beliefs about attributes of choice alternatives, discover the conditions under which certain states of the environment are more likely than others, and in so doing make sense of the world around them. Moreover, through social contacts individuals exchange information and form partly common aspirations, which may trigger actions to explore new alternatives.

The general framework considered dynamic formation of the choice-set. It integrates cognitive learning and social learning. In the proposed approach, cognitive learning focuses on updating beliefs about a non-stationary environment that will impact the expected utility of alternatives and habit formation, while social learning emphasizes on deriving and updating aspirations that may trigger re-evaluating currently known alternatives (exploitation) or search for new alternatives (exploration). The model and numerical simulation presented in this paper only covers cognitive learning. It provides a first step towards a fully operational model of dynamic formation of location choice-sets. In principle, the framework can be extended to a more complex system as we further explore in more detail how and to what extent social interactions influence people's behaviour that could be incorporated in defining and updating

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aspiration levels, as well as how people compose their expected outcome and make satisfaction evaluation. Furthermore, a similar framework can equally be used for modelling other choice (facets) and leaning behaviour involved.

Opmerking [H.J.P.13]: I think this should be updated?

Met opmaak: Tekstkleur: Rood

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Appendices

Table 1	Activation level of shopping locations
Figure 1	The choice making model
Figure 2	The general results of a basic case
Figure 3	The impact of mental effort limit
Figure 4	The impact of activation threshold
Figure 5	The impact of self aspiration threshold

Table 1 Activation level of shopping locations					
Contextual condition				Outcome	
Activity	Day-of-week	Origin location	Time-of-day	Location	Activation level
	*				
	*				
	*				
Shopping	Wednesday	Work	Non-peak	Shopping centre 1	10
				Shopping centre 2	10
				Shopping centre 3	80
	*				
	*				
	*				
Shopping	Saturday	Home	Peak	Shopping centre 1	100
				Shopping centre 2	20
				Shopping centre 3	10
Shopping	Saturday	Home	Non-peak	Shopping centre 1	30
				Shopping centre 2	60
				Shopping centre 3	10

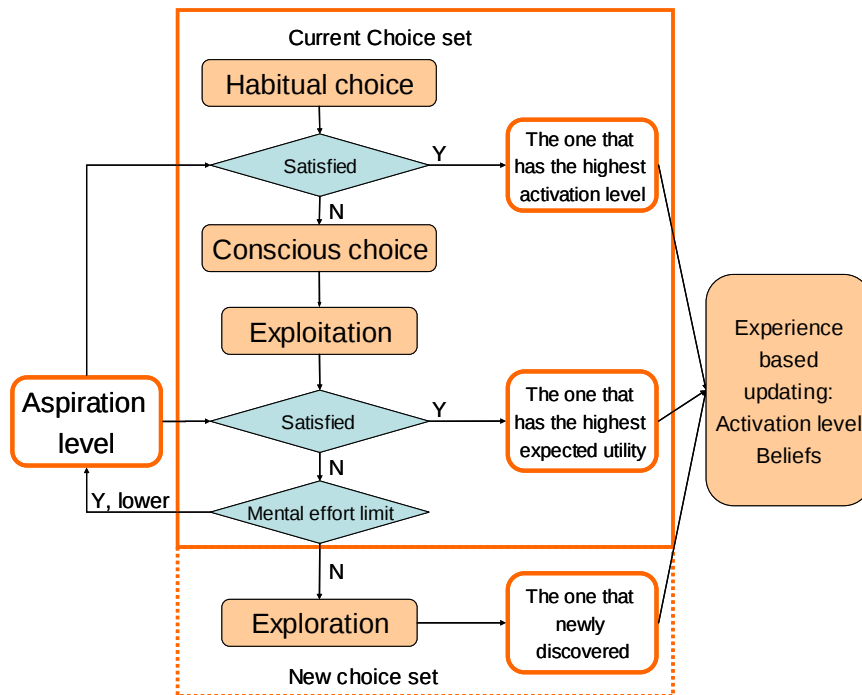


Figure 1 The choice making model

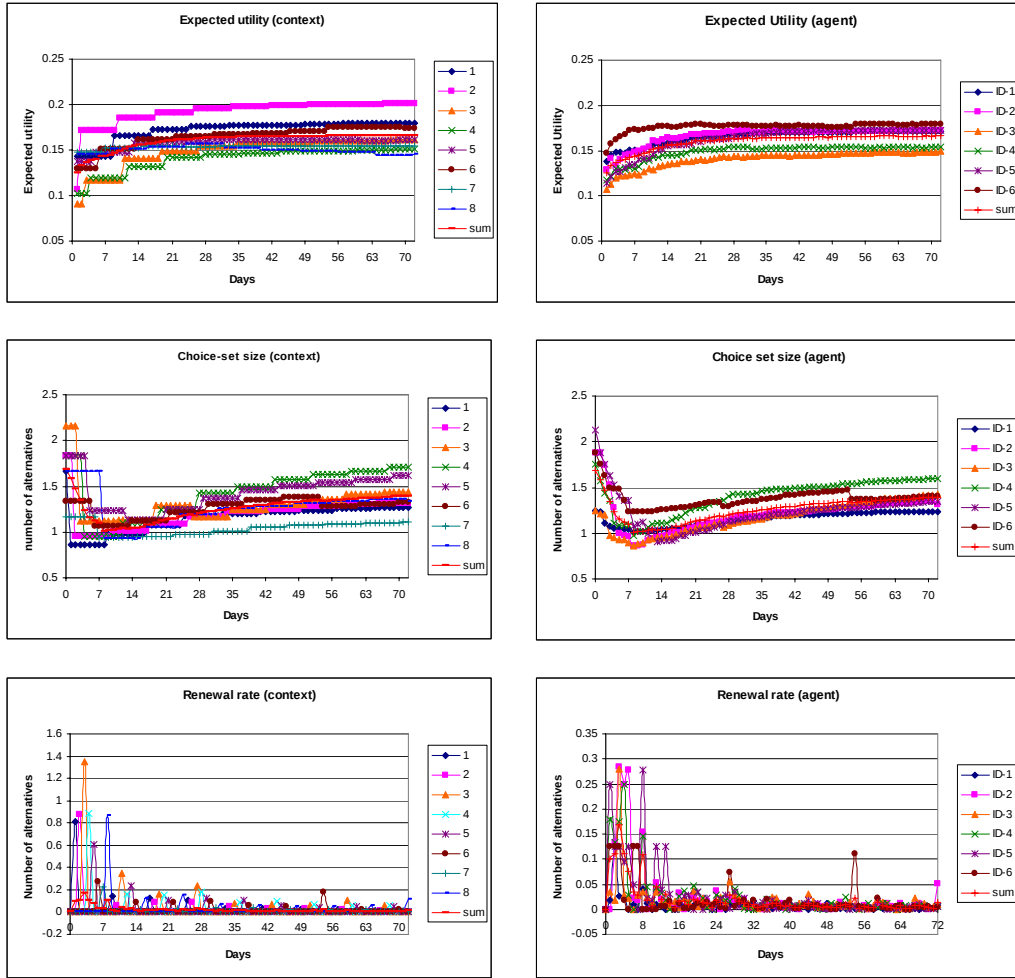


Figure 2 The general results of a basic case

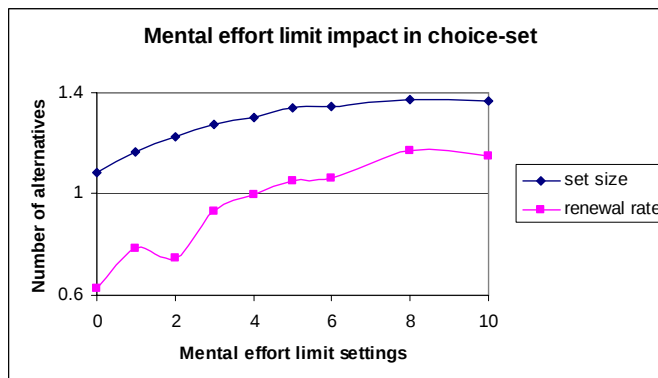
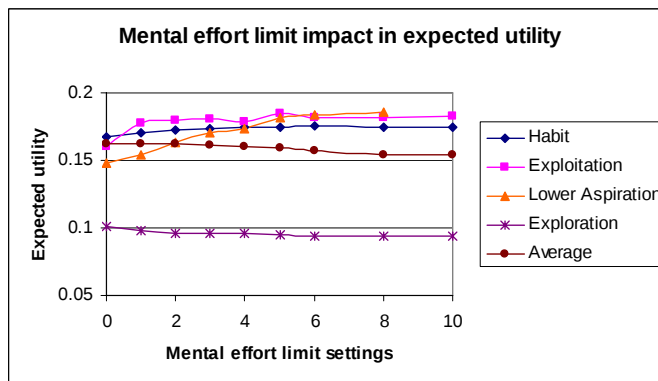
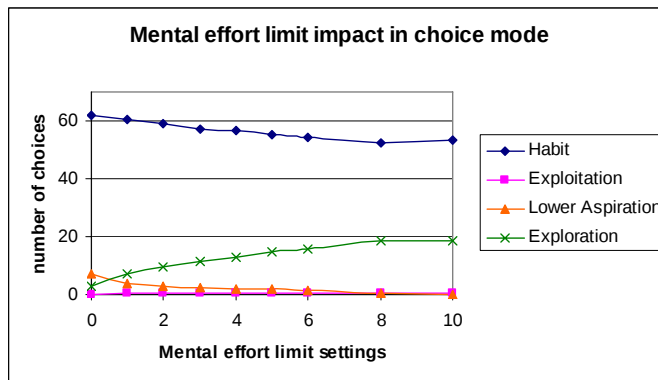


Figure 3a, b, c The impact of mental effort limit

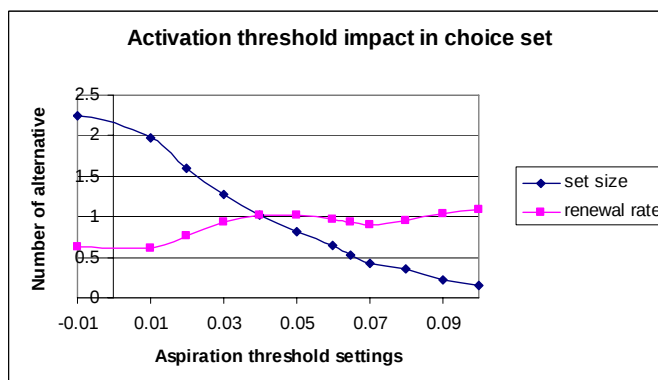
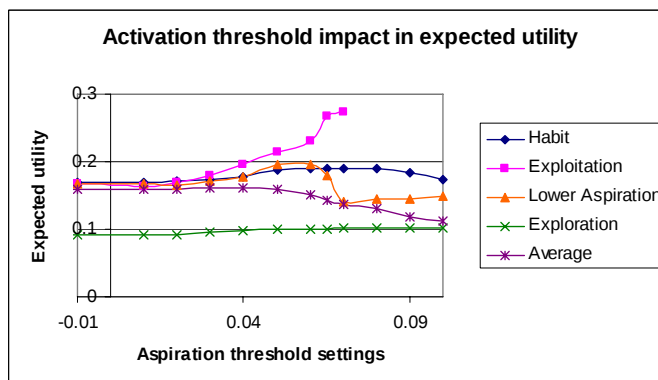
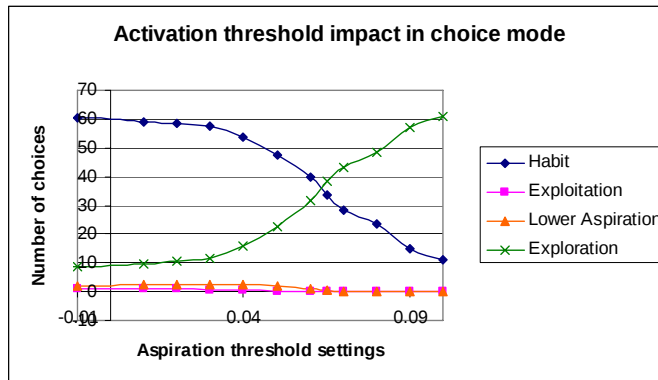


Figure 4a, b, c The impact of activation threshold

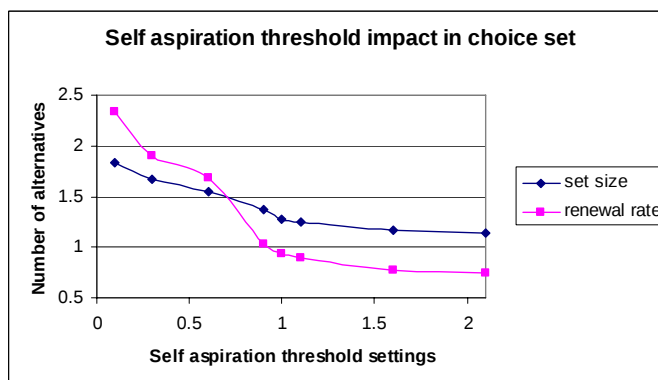
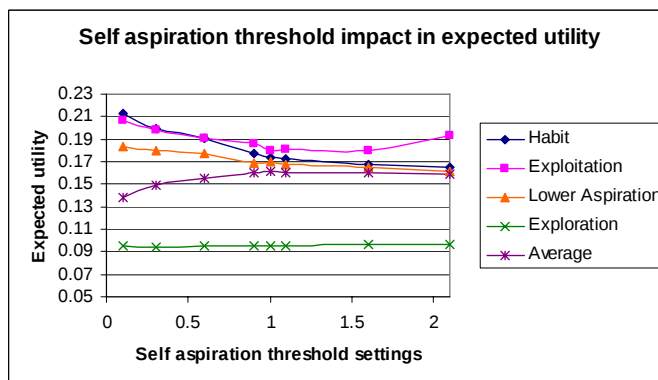
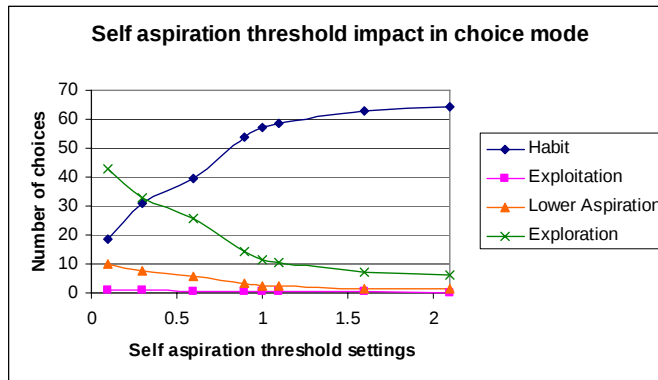


Figure 5a, b, c The impact of self aspiration threshold