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Modeling individuals' cognitive and affective responses in spatial learning behavior

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Abstract:
Activity-based analysis has slowly shifted gear from analysis of daily activity patterns to analysis and modeling of dynamic activity-travel patterns. In this paper, we describe a dynamic model that is concerned with simulating cognitive and affective responses in spatial learning behavior for a multi-agent system. By implementing activity-travel choices, agents observe the differences between actual experience and expectation, which may give rise to negative or positive emotions that influence the awareness of alternatives and, furthermore impact the evaluation of alternatives and hence choice behavior. As such, it provides an approach to model the dynamic process of rational and emotional mechanisms in the formation and adaptation of an individual's location awareness set, distinguishing habitual, exploitation and exploration modes of dynamic, context-dependent choice behavior. Principles of reinforcement learning and Bayesian perception updating are used. We demonstrate model properties using numerical simulation with a case study of shopping activity.

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1. INTRODUCTION

Now that comprehensive, operational activity-based models of transport demand have become available and are moving to practice (Timmermans, et al, 2002; Vovsha, et al, 2004; Pendyala, et al, 2005), the academic research community has started to address a new challenge: how to develop *dynamic* activity-based models of transport demand (Arentze and Timmermans, 2007). In this paper, we develop an agent-based model of dynamic location choice in the context of daily activity schedules.

The dynamic process by which an individual arrives at a choice decision is generally believed to be a process during which the formation of a choice set precedes the selection of an alternative. How an individual mentally constructs a situation is a key to how (s)he makes a decision. Decision styles may be highly dependent on contexts and on how people define the situation. If the environment is stationary, one might assume that as a result of repeated trials some steady state will be established: choice sets are stabilized and choices become habitual. However, in reality, the space-time and social environment is non-stationary and individuals' cognition of the environment may change as a result of new information from media, actual observation and social contact, which may prompt the individual to adjust situation structures and actively explore new alternatives. Also, the system is stochastic and by implementing choices, an individual may observe the differences between actual experience and expectation, which may give rise to negative or positive emotions that influence the rational evaluation of the alternative. When differences are profound, we may speak of critical incidents, i.e. events which may trigger individuals to change their choice. Under these circumstances, the actual performance of the choice for an individual may decrease below some critical level – the aspiration level of the individual, leading the individual to search for alternatives and adapt the current choice set, such that aspirations possibly can be achieved. Consequently, choice set formation is conditional upon context condition and dynamic in the sense that choice sets are updated each time an individual has experienced consequences of a choice or receives new information through other sources.

Using these concepts, this research looks at the role of learning in spatial behavior focusing on cognitive and affective responses to events in using and evaluating choice sets for a shopping activity. We conceptualize the creation of a choice set as context dependent, since different contexts may bring about different preferences, constraints, schedules, etc. In this study, the choice set refers to the set of discrete locations known by an individual, which is the subset of the universal set of locations of a study area for an activity. 'Known' means that the individual knows not only the physical location, but also the attributes that are potentially relevant for evaluation under specific contextual conditions in the decision making process.

In our system, individual travelers are represented as agents, which have a cognition of the urban and transportation environment, habits and activity-travel patterns. Agents are assumed to have aspiration levels associated with location attributes that in combination with evaluation results determine whether the agent will start exploring or persist in habitual behavior; an awareness level of each location alternative that determines whether or not the alternative is included in the awareness set in the next time step; an activation level of each location alternative that determines whether or not the alternative is qualified as a habitual choice, and an evaluation (utility) function that allows individuals to evaluate each location alternative given current beliefs about the attributes of the location (including travel time). Each of these elements is dynamic. Principles of reinforcement and Bayesian perception updating (Vanhulsel, et al, 2007; Han, et al, 2007) are used to simulate the dynamics of the system.

In the following, we will first describe dynamics in choice sets and choice behavior in terms of cognitive and affective response under uncertainty, continue with an illustration case using numerical simulations, and complete with a conclusion and discussion for future research.

2. THE MODEL

The model considers an individual making a location choice for a shopping activity. We assume that individuals will make decisions based on the perceived attributes of choice alternatives, as they have imperfect and incomplete information about the choice alternatives in their environment. Let $\boldsymbol{X}$ denote a set of attributes that describes a particular choice alternative, including a subset of temporally static attributes, $\boldsymbol{X}^s$, and a subset of dynamic attributes, $\boldsymbol{X}^d$, such as for example crowdedness.

We assume that for each dynamic attribute, $X_j^{d,t}$, the individual uses some classification, denoted as $X_j^{d,t} = \{x_{j1}, x_{j2}, \ldots, x_{jN}\}$, where $x_{j1} - x_{jN}$ represent possible states of $X_j^{d,t}$, and specifies his/her beliefs regarding a location *i* based on his/her current knowledge as a probability distribution across X_j^d denoted as $P_i^t(X_j^d)$, which sums up to 1. The degree of uncertainty is given by the degree of uniformity of $P_i^t(X_j^d)$. The state probabilities are conditional upon certain contextual variables, therefore we extend the probabilities $P_i^t(X_j^d)$ to $P_i^t(X_j^d|c)$, where *c* stands for a particular condition set of an universal set of relevant condition states. For example, crowdedness of a shopping location will depend on day-of-the-week and time-of-the-day. The expected utility of a choice alternative *i* for some context setting *c* and given a set of beliefs about the attributes of the location (including travel time) is then modeled as:

$$EU_i^t(c) = EU_i^s + EU_i^{d,t}(c) \quad (1)$$

$$EU_i^s = \sum_{j^s} \beta_{j^s} EX_{ij^s} \quad (2)$$

$$EU_i^{d,t}(c) = \sum_{j^d} \sum_n \beta_{j^d n} x_{j^d n} P_i^t(x_{j^d n}|c) \quad (3)$$

$$EUT_i^t(c) = EU_i^t(c) + \sum_n \beta_n^T x_n^T P_i^t(x_n^T|c) \quad (4)$$

where EU_i^t is the expected utility of choice alternative i at time t, $\beta_{j^s} EX_{j^s}$ is the expected partial utility of location *i* for static attributes j^s, $\beta_{j^d n} x_{j^d n} P_i^t(x_{j^d n}|c)$ is the expected partial utility of location i for possible state $x_{j^d n}$ with probabilities $P_i^t(x_{j^d n}|c)$ and preference $\beta_{j^d n}$ regarding dynamic attribute j^d with state *n* under condition *c*, and $\beta_n^T x_n^T P_i^t(x_n|c)$ is the expected utility of travel to location i for possible state x_n^T with probabilities $P_i^t(x_n^T|c)$ and preference β_n^T.

By implementing activities, individuals visit particular destinations and experience attributes, thereby reinforcing their beliefs and updating their memory traces (i.e., awareness) of alternative destinations in their environment. Regarding dynamic attributes, individuals update beliefs $P_i^t(X_j|c)$, using Bayesian principles and decision tree induction method as suggested in Arentze and Timmermans (2003). On a first level, this process involves incrementally updating the conditional probability distributions across the possible states for each observed attribute of the choice alternative after experiencing the actual states. On a second level, it involves periodically reconsidering whether the partitions of condition states that are mentally used to discriminate between contexts are still adequate or that this mental representation of condition states should be updated.

As the individual has limited information, when a choice is implemented, the individual experiences the actual state on each attribute, including all (quasi)-static variable, dynamic variables and travel. Moreover, some unexpected surprises might happen, for example, traffic congestion. Thus, the actual experienced utility is expressed as:

$$AUT_i^t(c) = \sum_j \sum_n \beta_{jn} x_{jn} K_{jn}^t + \varepsilon_i^t \tag{5}$$

where $K_{jn}^t = 1$, if the state of the attribute is actual experienced, and $K_{jn}^t = 0$, otherwise. ε_i^t is the surprise experienced by individual at location i at time t. We assume that when there is difference between the expected utility and the actual experienced utility, it gives rise to negative or positive emotions of the experience:

$$R_i^t(c) = AUT_i^t(c) - EUT_i^t(c) \tag{6}$$

where $R_i^t(c)$ is the emotional value of the event experienced at alternative *i* at time *t*. If the alternative has been visited several times, the emotional values of the experiences will accumulate to result in a positive or negative overall affective value associated with the alternative that may influence the awareness and perceived utility of the alternative:

$$E_i^t(c) = (1-\alpha_1)E_i^{t-1}(c) + \alpha_1 R_i^t(c) \tag{7}$$

where $E_i^t(c)$ is the emotional value of the alternative *i* at time *t*. $0 \le \alpha_1 \le 1$ is a parameter reflecting the trade-off between accumulated past emotional values and the most recent ones. When it approaches one, the value tracks the changing emotional value closer. This emotional value of the alternative may play a role in an overall perception of the evaluation of a choice alternative as follows:

$$EUE_i^t(c) = (1-\alpha_2)EUT_i^t(c) + \alpha_2 E_i^t(c) \tag{8}$$

where $EUE_i^t(c)$ is the overall expected utility of the alternative *i* at time *t*, including both a cognitive and an emotional component. $0 \le \alpha_2 \le 1$ is a parameter reflecting the trade-off between rational behavior (based on expected utility) and affective behavior (based on emotional value).

Dynamics on the level of awareness of choice alternatives are contingent on the event memory of the alternative and follow the processes of memory decay and refreshment. Let $S_i^t(c)$ be the awareness level of an alternative i at time *t* under condition *c*, and ω be a minimum awareness level for event memory retrieval ability. The awareness of an alternative *i* at time *t* under influence of strength of a memory trace of events experienced at the alternative equals:

$$S_i^t(c) = \begin{cases} \max(\lambda_1 S_i^{t-1}(c), \left|R_i^t(c)\right|) & \text{if } I_i^t = 1 \\ \lambda_1 S_i^{t-1}(c) & \text{otherwise} \end{cases} \tag{9}$$

where $I_i^t = 1$, if the alternative *i* was chosen at time t, and $I_i^t = 0$, otherwise, and $0 \le \lambda_1 \le 1$ is a parameter representing the awareness retention rate that indicates the speed with which the memory of the event is faded. The stronger the emotional impact of the event experience, the longer it stays in memory, and the awareness of the concerning alternative increases if the emotional impact is stronger than the current level. $R_i^t(c)$ is the emotional value attributed to alternative i that is calculated using Eq. 6. At every time *t*, an awareness-set will consist of those alternatives which awareness level exceeds a threshold, reflecting limited human memory retrieval:

$$\Phi^t(c) = \{i \left| S_i^t(c) \ge \omega\right.\} \tag{10}$$

Thus at every moment in time when individuals have to consider a particular situation, they hold a set of context-dependent beliefs about the state of the alternatives in their awareness-set. This awareness-set consists of a subset of all choice alternatives in their environment with a differentiating context-dependent awareness level. Only the alternatives that are aware of in a given context will be considered and constitutes a choice set in that context.
Dynamics on a complementary value of the choice alternatives are contingent on the action

rewards the alternative gives when chosen and also follow the processes of reinforcement learning. The strength of a trace in a memory of actions, called activation level here, of a particular alternative *i* in the choice set is modeled as:

$$W_i^{t+1}(c) = \begin{cases} W_i^t(c) + \gamma AUT_i^t(c) & \text{if } I_i^t = 1 \\ \lambda_2 W_i^t(c) & \text{otherwise} \end{cases}, \quad \text{where} \quad i \in \Phi^t(c) \tag{11}$$

where $I_i^t = 1$, if the alternative was chosen at time t, and $I_i^t = 0$, otherwise, $0 \le \gamma \le 1$ is a parameter representing a recency weight, which is relevant only when the alternative is chosen; and $0 \le \lambda_2 \le 1$ is a parameter representing the retention rate. $AUT_i^t(c)$ is the utility attributed to alternative i that is calculated based on Eq. 5. Note that, condition states used for updating awareness level or activation levels may not be the same as condition states used for updating attribute beliefs.

The inclination to explore depends on an agent's satisfaction with available alternatives in his/her choice set. Satisfaction in turn depends on the agent's aspiration level. Aspiration levels are defined at the level of choice alternative attributes and gives 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 current aspiration value for an attribute *j* at time *t* as $AX_j^t(c)$, where as before *c* is a particular condition state.

Evaluating a choice alternative requires mental effort, depending on the degree of involvement in the decision process, which in turn will also be context-dependent. To avoid needless mental effort agents develop habits. Accordingly in our model, an agent is assumed to always first consider the alternative that has the highest activation level in the choice set, i.e., the alternative that is most easily retrieved from (action) memory and thus requires least mental effort. This habitual behavior is displayed provided that the alternative concerned satisfies aspiration levels. The outcome of a comparison between aspiration and expected outcome given current beliefs marks a switch of choice mode from habitual behavior to a conscious choice. We assume that if dissatisfaction (i.e., the difference between aspiration and expected outcome) regarding at least one attribute exceeds a tolerance range, δ_j, an agent will switch to another mode of behavior and starts searching consciously for better alternatives. A large tolerance range indicates that the agent strongly dislikes the mental effort involved in finding better actions and is easier satisfied with the current situation. Vice versa, a small tolerance implies that an agent sets higher standards in what is found acceptable or has a higher propensity to explore. Formally, habitual choice implies:

$$i^*(c) = \arg\max_i W_i^t(c), \quad \text{if } EX_{i^*j}^t(c) - AX_j^t(c) \le \delta_j \forall j \tag{12}$$

$$EX_{ij^d}^{d,t}(c) = \sum_n x_{j^d n} P_i^t(x_{j^d n} | c) \tag{13}$$

Where $i^*(c)$ is the chosen alternative under condition c, and $EX_{ij^d}^{d,t}(c)$ is the expected attribute level for dynamic attribute *j*.

Next, when acting in a conscious mode, agents will first be engaged in exploitation in the sense that they will search for a better alternative in their current awareness-set. An agent is assumed to choose the alternative with the highest expected utility (including emotional value) provided that it does not violate the tolerance threshold for any attribute of aspiration, relevant for the decision. Formally, exploitation choice can be expressed as:

$$i^*(c) = \arg\max_i EUE_i^t(c), \quad \text{if } EX_{i^*j}^t(c) - AX_j^t(c) \le \delta_j \forall j \tag{14}$$

This may lead to the recognition that a different choice alternative outperforms habitual choice (this may happen if the habitual alternative deteriorated over time). If (also) dissatisfaction for at least one attribute of the alternative with the highest expected utility in the current choice set exceeds the tolerance threshold, the individual will start and explore new alternatives beyond the current choice set. This process of exploration is not random, but goal-directed in the sense that the exploration process will be guided by the attributes that caused dissatisfaction. Simulating not the process of exploration, but the outcome of this process, the probability that a location i is discovered is specified as:

$$P^t(i|c,J') = \frac{\exp(V_i^t(c,J')/\tau)}{\sum_{i'} \exp(V_{i'}^t(c,J')/\tau)} \tag{15}$$

$$V_i^t(c,J') = \sum_{j\in J'} EUT_{ij}^t(c)\ , \ where \begin{cases} J' = \{ j | EX_{i*j}^t(c) - AX_j^t(c) > \delta_j \} \forall j \\ i*(c) = \arg\max_i EUE_i^t(c) \end{cases} \tag{16}$$

where $EUT_{ij}^t(c)$ is a true expected value, and V_i^t is the utility measure of alternative i of a universal set concerning the dissatisfied attributes j and travel distance involved, and τ is a parameter reflecting the availability of information in the selection of new locations.

In addition, we assume that when the effort, ϖ, involved in search for a better alternative is built up and exceeds a predefined maximum, $\varpi_{\max}$, instead of continuing exploring, the agent will avoid further frustration by lowering his/her aspiration level(s) (realizing that the current aspiration level(s) are not realistic). By replacing the current aspiration levels with the attribute levels of the alternative that currently has the highest expected utility, the agent will assure a relatively optimal outcome and maintains high aspiration levels for future choices:

$$AX_j^t(c) = EX_{i*j}^t(c)\ , \ \begin{cases} if \quad \varpi > \varpi_{\max} \\ where \quad i* = \arg\max_i EUE_i^t(c) \end{cases} \tag{17}$$

In doing so, the alternative that currently has the highest expected utility will be chosen and beliefs of all the relevant attributes of this alternative will be updated based on experience.

As a consequence of the above mental and physical mechanisms, an agent arrives at a selection of a single alternative location each time an activity is to be carried out. Depending on aspiration levels and experiences, 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 was newly discovered (conscious exploration choice).

3. ILLUSTRATION

To examine the behavior of the model a series of numerical simulations were conducted. Due to space limitations, the simulations discussed here focus on one activity – shopping, and test the general model performance and the effects of one particular parameter, α_2, that focuses on the aspect of trade-off between cognitive rational response and affective response in spatial learning behavior.

3.1 Simulation settings and process

The simulation considers an area of 100 by 100 cells of 100 meter by 100 meter in size. There are 12 shopping locations including 6 small, 4 medium and 2 big shopping centers. The locations of these shopping centers are predefined and spread across the study area. There are 6 agents each with a predefined residential location and work location respectively. These locations are the origins of the agents' shopping trips. The input schedule of the 6 agents is arbitrary generated and specifies only one shopping activity a day for a period of 72 days in total. Eight context conditions are distinguished as combinations of day of the week (weekday vs. weekend), time of day (rush hour vs. non-rush hour), and origin location (from home or from work). The conditions have as much as possible equal probability for a shopping trip in the schedules of the agents. Six static attributes of shopping centers are included: 1) the size of the shopping centre (big, medium, or small), 2) stores for daily goods are present (yes or no), 3) stores for semi-durable goods are present (yes or no), 4) stores for durable goods are present (yes or no), 5) price level (high, middle or low), and 6) parking space (yes or no). Furthermore, (only) one dynamic attribute – crowdedness is included with four states as (No, Little, Medium, Very). Travel time is measured as straight-line distance at this stage. The initial knowledge of each agent is based on a pre-period 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 surprise term that agents experienced for actual utility is generated using normal distribution with mean 0 and standard deviation of 0.25.

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 for example 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 awareness and 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 and based on the experience, the agent updates its knowledge/memory including an emotional value, awareness, activation level and beliefs about the state of the environment regarding the alternative chosen. The condition learning part is left out of consideration. Only the conditional learning is considered. For every agent, the basic setting is: 1) the awareness threshold $\omega = 0.05$, the parameter for awareness retention rate $\lambda_1 = 0.9$, 2) the parameter for updating activation levels $\gamma = 0.99$ and $\lambda_2 = 0.2$, 3) the maximum exploration effort is 3 units, 3) the aspiration dissatisfaction tolerance $\delta = 1$ and the uncertainty parameter for exploration $\tau = 1$.

3.2 Some results

Figure 1 shows the results of the basic case with $\alpha_2 = 0.2$ for two typical simulated agents (denoted as D1 and D2) on 3 indicators: a) average expected utility of the choice set, b) choice set size, and c) renewal rate (for the specific contextual condition that a decision is made). As expected, the average expected utilities of the choice set are not constant across the 72 days. The size of the choice set is not fixed, but shows a tendency to slightly increase. The range in the size is reasonable with an average of around 2.24 locations for each context and each agent. The waving curve showing the renewal rate reflects dynamics of the choice sets that follows from adding newly discovered alternative to the choice set and discarding ones that have not been chosen for a long time. On average across 72 choice occasions there are 56.42 habitual choices with an average expected utility value of 0.138, 5.91 exploitation choices with an average expected utility value of 0.135, and 9.17 exploration choices with an average utility value of 0.094. As it turns out, the expected utility of exploration choice is the lowest on average, because of the limited information in the search for good alternatives.

A detailed example of a dynamic process of one agent with nine consecutive choices under the same context condition is shown in Figure 1 on the right lower corner. The example started with an exploration choice, which took place as there was no alternative in the current choice set that could satisfy the aspiration level of each attribute. After three time continuous explorations, there was still no new satisfactory alternative found. Then, the aspiration level was decreased as the agent realized that the aspirations are not realistic. Lowering aspirations brought the possibility of exploitation, to find within the current choice set an alternative that now meets the (lowered) aspirations. The alternative chosen as an outcome of exploitation became the habitual choice in the later choice occasions. The expected utilities of habitual choices are slightly decreasing as the consequence of the non-stationary environment.

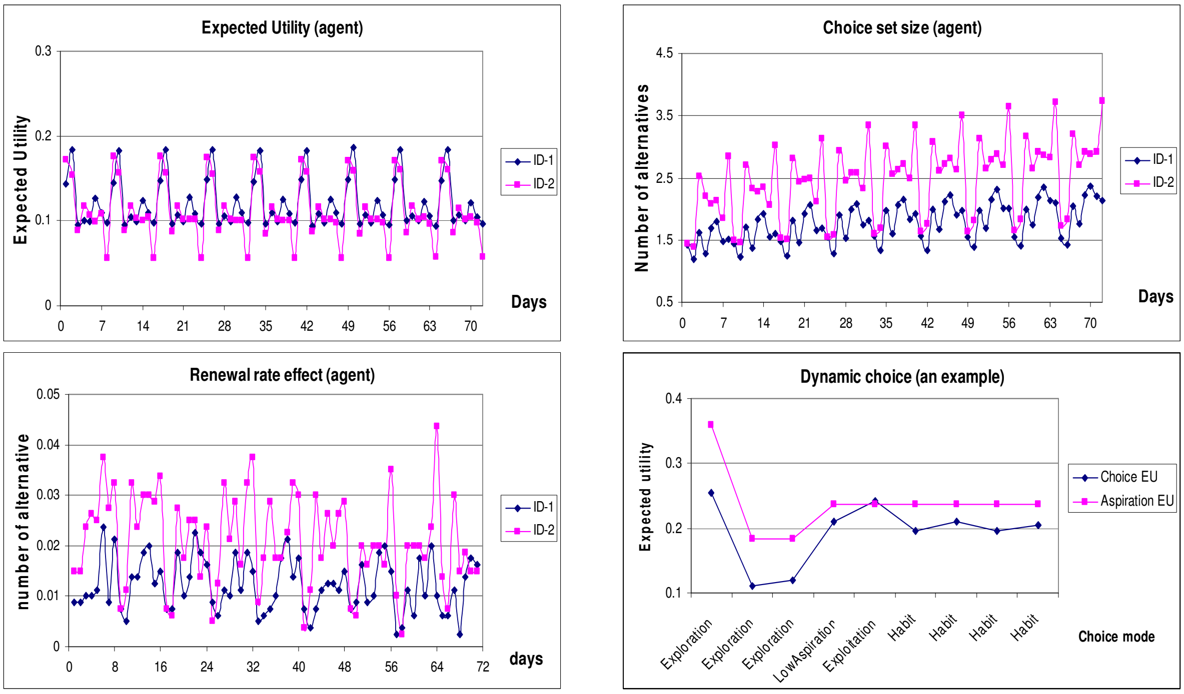

Figure 1 The general results of a basic case

Figures 2 shows impacts of emotional value across choice events across runs on a) the average frequency of choice mode, b) the expected utility of the different choice modes, c) the size and the renewal rate of the choice set, and d) the average expected utility of choice and choice sets respectively. Figure 2a shows that frequency of exploration behavior increases with weight of emotional value in evaluation. This suggests that a higher influence of affective response and less control on the basis of rational judgments in choice making tends to lead to spending more effort in exploring new alternatives. These imply two possibilities. On the one hand, when experienced negative emotion, agents have a high chance in the next choice to explore. On the other hand, when experienced positive emotion, the alternative may not necessarily structurally perform good, which also bring the possibility in next choice to explore. As the exploration behavior increases, habitual behavior decreases. Because more exploration increases the possibility to discover a new alternative that may satisfy aspiration levels, the frequency of lowering aspiration levels declines slightly.

The eye-catching features in Figure 2b and 2d are the declining trend lines of the expected utility in almost all choice modes except exploration as well as in the average expected utility of choice sets. There are a number of possible explanations. First, one might suspect that as the consequence of the simulation settings. The overall utility includes both rational expected utility and emotional impact. As the weight of rational expected utility approximates 0, and the weight of emotional impact approximates 1, the overall expected utility will trace emotional impact more, which by definition has mean 0. Therefore in the long run, if emotional impact dominates the overall expected utility, the average utility will get close to 0, as shown in the Figures. A second explanation may be that negative emotions bring with it avoiding behavior. Every time a preferred alternative performs worse than expected, giving rise to a negative emotion value, the second best one become the first candidate for the next choice occasion, which may in fact has poorer structural performance. As the originally preferred alternative will not be chosen, its expected utility will not be updated, and it will not recover from the negative shock. As a consequence of not being chosen for a long time, it disappears from the current choice set. Then, it may find its way back only through exploration choice. The same process will be repeated for the second structurally best alternative and so on. Thus, through this process the expected utility of habitual and exploitation choice will decrease consistently over time in cases where the weight of emotion impact is large.

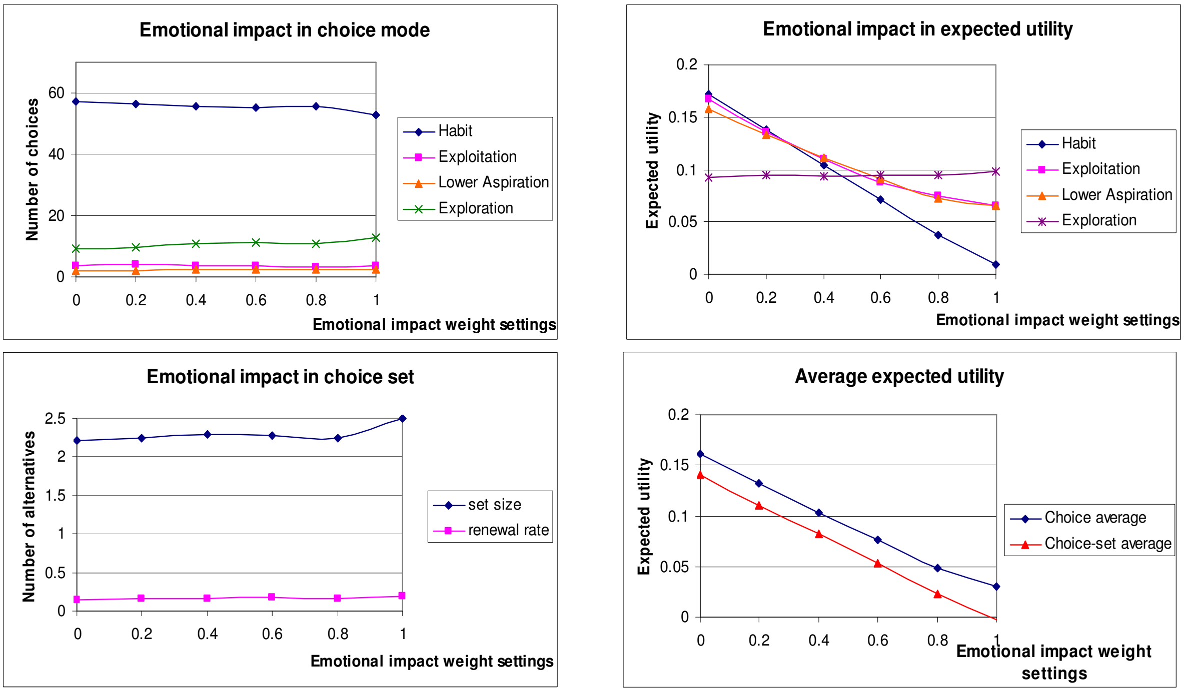

Figure 2 The impact of affective response

Thus, strongly emotionally driven choice behavior, according to this model, leads to a decline in welfare over time. In reality, several other mechanisms (that easily could be built into the model) may play a role that would counteract such a tendency. First, based on random factors there may be a positive probability of revisiting a location, even when it has a negative association. This could be captured by a stochastic utility component in the model. Second, agents may be able to block their emotion in an exploitation mode and, hence, evaluate choice alternatives purely based on rational considerations. Third, it is to treat emotion impact as an additional component of the overall expected utility, not as a complementary component with a shared total weight of 1 between cognitive expected utility and emotional value.

As it turns 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 higher than habitual choice. The expected utility of exploration choices is not affected by the weight of emotion because the probability of discovering particular alternatives is not associated with emotional impact weight. As Figure 3c shows, increasing emotional impact weight implies more exploration, and therefore the size and the renewal rate of the choice set slightly increase.

As these simulations indicate, the emerging patterns of choice mode frequency, expected utility of different choice modes, size and renewal rate of the choice sets appear to respond in relatively unique ways to proposed parameters of the model. As it turns out, the model is capable of distinguishing habitual choice, exploitation choice and exploration choice. It provides a modeling approach for simulating habit formation and adaptive behavior.

4. CONCLUSION AND DISCUSSION

Simulations indicate that solutions generated by the model are sensitive to aspects of rational and emotional considerations in choice making in well-interpretable ways. The result of these behavior mechanisms are the evolution of choice sets and choice patterns, reflecting emergent behavior in relation with non-stationary environment. Our approach is scalable in the sense that it is applicable to study areas of large size (e.g., region wide). As expected, knowing the awareness set from which a choice is made may provide a parsimonious way in large scale micro-simulation in the areas of activity-based travel-demand modeling and integrated land-use – transportation systems. Some applications are straightforward. For example, conditions can be simulated under which learning leads to habitual behavior as well as what happens when moving to a new city. Likewise, the optimal location of a new shopping centre can be simulated. Also, spatial effects of the new shopping centre opening can be observed.

The dynamic model described in this paper focuses on spatial learning behavior of agents regarding their experiences and perceptions with the transportation systems and changes in the environments. Dynamics may also result from changing needs in response or in anticipation of lifecycle events, critical events and new information from media and social contacts. The properties of dyad relationships within a social network may also influence dynamics of awareness of and knowledge about alternatives. Social learning plays a role not only in deriving and updating aspirations that may temporally break habitual behavior and trigger a search for new alternatives, but also in adjusting preference values. As such, the framework could be extended to integrate social learning with cognitive and affective response in spatial learning behavior.

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