HABIT FORMATION AND AFFECTIVE RESPONSES IN LOCATION CHOICE DYNAMICS

Qi Han, Urban Planning Group, Eindhoven Technical University, q.han@tue.nl

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

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

ABSTRACT

This paper discusses the development of a dynamic agent-based model which simulates how agents search and explore in non-stationary environments and ultimately develop habitual, context-dependent, activity-travel patterns. In this paper, we specifically focus on how *emotional* values, beliefs and aspirations can be incorporated in these models. Next, through an illustrative case study, we will show how these can be integrated in an agent-based micro-simulation to model dynamic decision making under uncertainty and illustrate that people try to avoid higher uncertainty in their location choice. Simulations indicate that solutions generated by the model are sensitive to rational and emotional considerations in decision making in well-interpretable ways. Our approach is scalable in the sense that it is applicable to study areas of large size (e.g., region wide).

Keywords: habit formation, emotional value, location choice, learning

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 real-world 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 habitual behavior and actively explore new alternatives. Also, the system is stochastic and by implementing choices, an individual may observe 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 behavior. Under these circumstances, the utility that an individual derives from habitual choice 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 may be achieved. Consequently, choice-set formation is conditional upon context and dynamic in the sense that choice-sets are updated each time an individual has experienced the consequences of a choice or received 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 being 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 a 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 cognitive representation 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 qualifies 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 X denote a set of attributes that describes a particular choice alternative, including a subset of temporally static attributes, X^s, and a subset of dynamic attributes, 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 a universal set of relevant condition states. For example, crowdedness of a shopping location will depend on day-of-the-week and time-of-day. The expected utility of a choice alternative *i* for some context setting *c* , given a set of beliefs about the attributes of the location (including travel time), is then modeled as:

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

$$EU_i^s = \sum_{j^s} \beta_{j^s}^s EX_{j^s}^s \tag{2}$$

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

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

where EU_i^t is the expected utility of choice alternative i at time t, $\beta_{j^s}^s EX_{j^s}^s$ is the expected partial utility of location *i* for static attributes j^s, $\beta_{j^d n} x_{j^d n} P_{ij^d}^t(x_{j^d n}|c)$ is the expected partial utility of location i for possible state $x_{j^d n}$ with probabilities $P_{ij^d}^t(x_{j^d n}|c)$ 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 closer tracks the changing emotional value. This emotional value of the alternative may play a role in the 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:

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

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:

$$\Phi^t(c) = \{i \mid S_i^t(c) \geq \omega\} \tag{10}$$

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 an individual is 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 memory trace 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, $0 \leq \gamma \leq 1$ is a parameter representing a recency weight, which is relevant only when the alternative is chosen; and $0 \leq \lambda_2 \leq 1$ 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 give direction to exploration processes (e.g., find alternative stores with a lower price level rather than find stores that have higher utility) and serve as subjective reference points, which determine 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:

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

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

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:

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

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 attributes levels of the alternative that currently has the highest expected utility, the agent will assure a relatively optimal outcome and maintain 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 and given the focus of the present paper, the simulations discussed here focus on one activity – shopping, and test general model performance that reveals the dynamics of habit formation and affective responses in spatial learning behavior. This simulation consists of two parts: 1) an existing situation with 12 shopping locations tested for 8 different scenarios and, 2) a situation with a new shopping location added.

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. 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 an 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, defined as {No, Little, Medium, Very}. Travel time is calculated as physical 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 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 other context conditions used to define 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 emotional value, awareness, activation level and beliefs about the state of the environment regarding the chosen alternative. The condition learning part is left out of consideration. Only conditional learning is considered. For every agent, the basic setting is: 1) the awareness threshold $\omega = 0.07$, 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 $\tau = 1$, 4) the parameter for balance between accumulated past emotional value and the most recent ones $\alpha_1 = 0.2$, the parameter for trade-off between rational behavior (based on expected utility) and affective behavior (based on emotional value) $\alpha_2 = 0.2$. The surprise term that agents experienced for actual utility is generated using a normal distribution with mean $\mathrm{E} = 0$ and standard deviation $std = 0.25$. The first scenario is the baseline. The remaining scenarios vary in emotional impacts (see Table 1 for detailed scenario settings and some of the simulation results).

3.2 Scenarios and results with the existing situation

Table 1 shows the detailed scenario settings and some of the simulation results regarding the situation of 12 shopping locations. Figure 1 illustrates the impact of different scenario settings of emotion impact on choice mode frequency (1a) average expected utility of choice set and chosen alternatives under different choice modes (1b), average size of choice sets and average renewal rate of choice sets (1c), and average number of agents who know the location (1d) respectively.

As it turns out, each scenario has a different behavior pattern compared to scenario 1, the baseline, in various respects. In scenario 2, as expected, the frequency of exploration behavior increases with the weight attached to 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. This may imply two things. On the one hand, when experiencing negative emotion, agents have a high chance in the next choice to explore. On the other hand, when experiencing positive emotion, the alternative may not necessarily structurally perform well, which also brings the possibility in next choice to explore. As exploration behavior increases and habitual behavior decreases, the choice set size and renewal rates increase. The average expected utility of choices and choice-sets are the lowest among all scenarios, because of the higher ratio of emotional value in the evaluation.

When the emotional value is influenced more by tracking the more recent events (See scenario 3), the number of habitual choices decreases and the number of exploration choices increases. The number of alternatives in the choice set and renewal rates are bigger. The average expected utility of choices and choice-sets stay more or less the same.

Table 1 Scenario settings and its results with the existing situation

Scenario	Settings		Results						
	Type of emotional impact	Parameter	Choice mode frequency (its average expected utility)			Set size	Renewal rate	Choice average	Choice set average
			Habit	Exploitation	Exploration				
1	Baseline case	--	65.09 (0.31)	3.24 (0.31)	3.67 (0.27)	2.07	0.10	0.31	0.27
2	Emotional decision	$\alpha_2 = 0.6$	63.88 (0.15)	3.69 (0.17)	4.43 (0.28)	2.12	0.12	0.16	0.13
3	Recent emotions	$\alpha_1 = 1.0$	63.84 (0.30)	3.30 (0.32)	4.87 (0.28)	2.15	0.12	0.30	0.27
4	Short memory	$\lambda_1 = 0.8$	65.75 (0.30)	2.82 (0.31)	3.42 (0.28)	1.54	0.15	0.30	0.28
5	Negative surprises	$\varepsilon \leq 0$	64.70 (0.29)	3.25 (0.30)	4.05 (0.27)	2.00	0.13	0.29	0.26
6	Positive surprises	$\varepsilon \geq 0$	65.15 (0.32)	3.02 (0.32)	3.83 (0.28)	1.88	0.13	0.32	0.29
7	Higher fluctuate surprises	$std = 1.0$	58.20 (0.31)	8.61 (0.33)	5.19 (0.28)	2.49	0.09	0.31	0.27
8	Negative mean surprises	$\mathrm{E} = -0.2$	62.92 (0.28)	4.79 (0.28)	4.29 (0.27)	2.29	0.10	0.28	0.25

With a short memory of emotional impact, the number of choice alternatives in the choice set is the lowest across all scenarios, while the renewal rate of the choice set is the highest. It also has a great effect on location knowledge: almost every location is known by the least number of agents. The number of explorations show subtle changes as the remembered alternatives are really good ones and more often qualify for habitual choices.

When the uncertainty that contributes to emotional impact only involves negative surprises, the average expected utility of choices is lower. As a consequence of negative surprises, the renewal rate of the choice-set is higher. It suggests that negative surprises trigger more exploration, because alternatives within the current choice set may not perform consistently well (see scenario 5). In contrast, in scenario 6, when the emotional value only covers positive surprises, the number of habitual choices and the average expected utility of choices are the highest. The choice set is smaller. It implies that positive emotional memory helps in forming habits. The knowledge of different location deviates more between agents as shown in the number of agents knowing the location, because agents tend to stick to their choices.

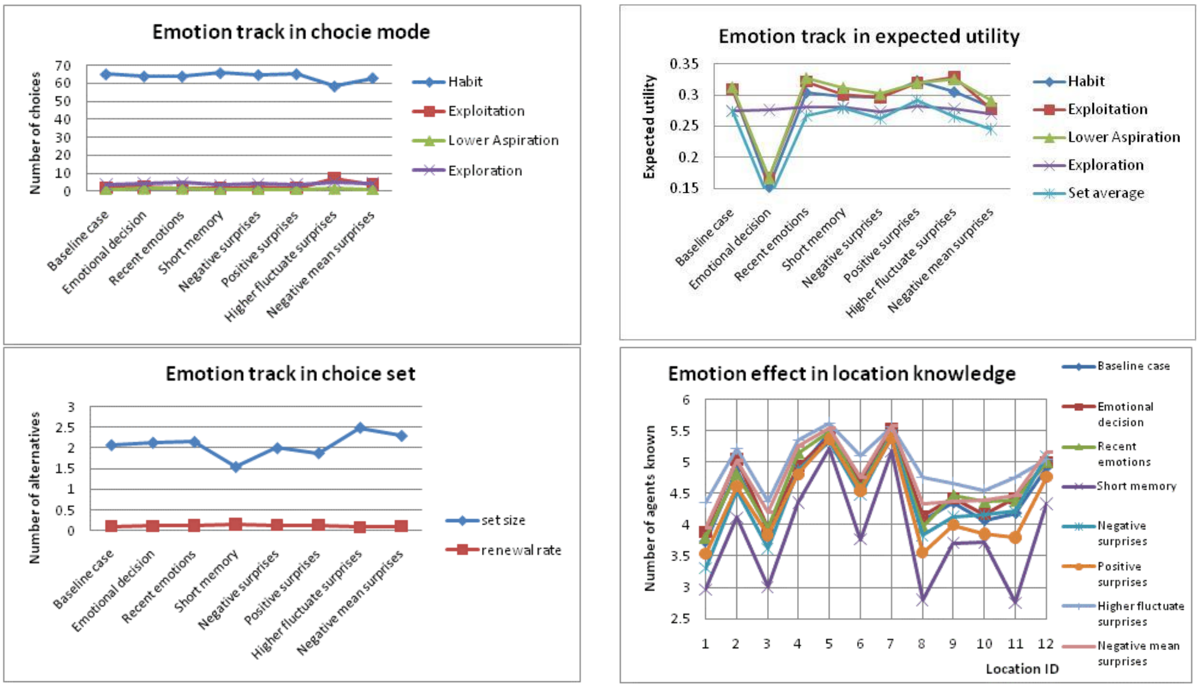

Figure 1 The impact of emotional impact with existing situation

Moreover, when the uncertainty is higher in terms of higher fluctuating surprises as shown in scenario 7, the number of habitual choice is the lowest, while the number of explorations is the highest. It is not a surprise that the number of exploitations is the highest, because with higher level of surprises, agents may keep in mind for a longer time those alternatives that once performed well. With higher level of uncertainty, the location knowledge is more equally spread across all 6 agents as shown in the number of agents knowing each location and in the number of alternatives in the choice-sets. It reveals that agents are aware of more locations because of the higher level of uncertainty. However these locations may not be strictly associated with positive memory or always perform well. Therefore, it may trigger more exploration.

Furthermore, in scenario 8 when the uncertainty is associated with negative mean surprises (that is to say on average the experiences are worse than expectations), the number of habitual choices is lower, and the number of explorations is higher. The eye-catching features are the lower average expected utilities of choices for all choice modes except exploration and the lower average expected utility of choice sets. It also has an effect on location knowledge as the negative surprises are contributed to a higher number of choice sets, but lower number of renewal rates.

3.3 Scenarios and results with a new shopping location added

Table 2 shows the detailed scenario settings for the newly added shopping location (13^{th}) that appears from day 25 onwards in addition to the 12 existing locations. Figure 2 illustrates the influence of different settings of emotion impact regarding the 13^{th} shopping location on choice mode frequency (2a) average expected utility of choice set and chosen alternatives under different choice modes (2b), average size of choice sets and average renewal rate of choice sets (2c), and average number of agents who know the location (2d).

Table 2 Scenario settings and its results with a new shopping location added

Scenario	Settings		Results						
	Type of emotional impact	Parameter	Choice mode frequency (its average expected utility)			Set size	Renewal rate	Choice average	Choice set average
			Habit	Exploitation	Exploration				
1	Baseline case	--	65.09 (0.31)	3.24 (0.31)	3.67 (0.27)	2.07	0.10	0.31	0.27
2	New shop standard	$std = 0.25$ $\mathrm{E} = 0.0$	67.70 (0.31)	2.51 (0.32)	1.79 (0.28)	1.99	0.09	0.31	0.28
3	New shop Bigger surprises	$std = 1.0$	67.25 (0.31)	2.89 (0.33)	1.78 (0.29)	2.00	0.08	0.31	0.28
4	New shop Poor performance	$\mathrm{E} = -0.2$	67.46 (0.28)	2.76 (0.32)	1.87 (0.28)	1.99	0.09	0.31	0.28

As it turns out, when a new shopping location is added, the shopping behavior pattern is compared differently to the baseline case (scenario 1). In this case, the new shopping location is located in the middle of the study area. It is big and provides daily, semi-durable and durable goods with a medium price level. It has limited parking place and normal crowdedness. Theoretically, it should have a relatively good structural performance, if the surprise it brings has the same settings as those for all other locations as shown in scenario 2.

In line with our expectations, in scenario 2, the number of habitual choice increases and the number of exploitations and explorations decreases. The expected utility of choice increases especially for exploitation and exploration modes as the newly added location is found and entered into the choice set of agents. With the structurally good performance, the newly found location helps in bringing down the size of the choice set and the renewal rate. Since the new location starts to appear on day 25, when the simulation ends on day 72, the process of habit formation has not reach its steady state. A detailed check of the process reveals that the new location often first enters an agent's choice set as an exploration choice, after that as an exploitation choice, and then it may become a habitual choice if it has been visited several times. As a result, the location knowledge also changes, as some locations become less popular and are replaced by the newly added one.

When the newly added shopping location has bigger surprises as shown in scenario 3, the number of exploitation choice increases, while the number of renewal rate decreases. It has the highest expected utility of exploitation choices. Since a bigger surprise means higher emotional impacts, agents may remember it for a longer time and make it an exploitation choice in the subsequent decisions. With higher level of uncertainty, the number of agents knowing the new location is the highest although it may not be chosen if it associated with negative emotions.

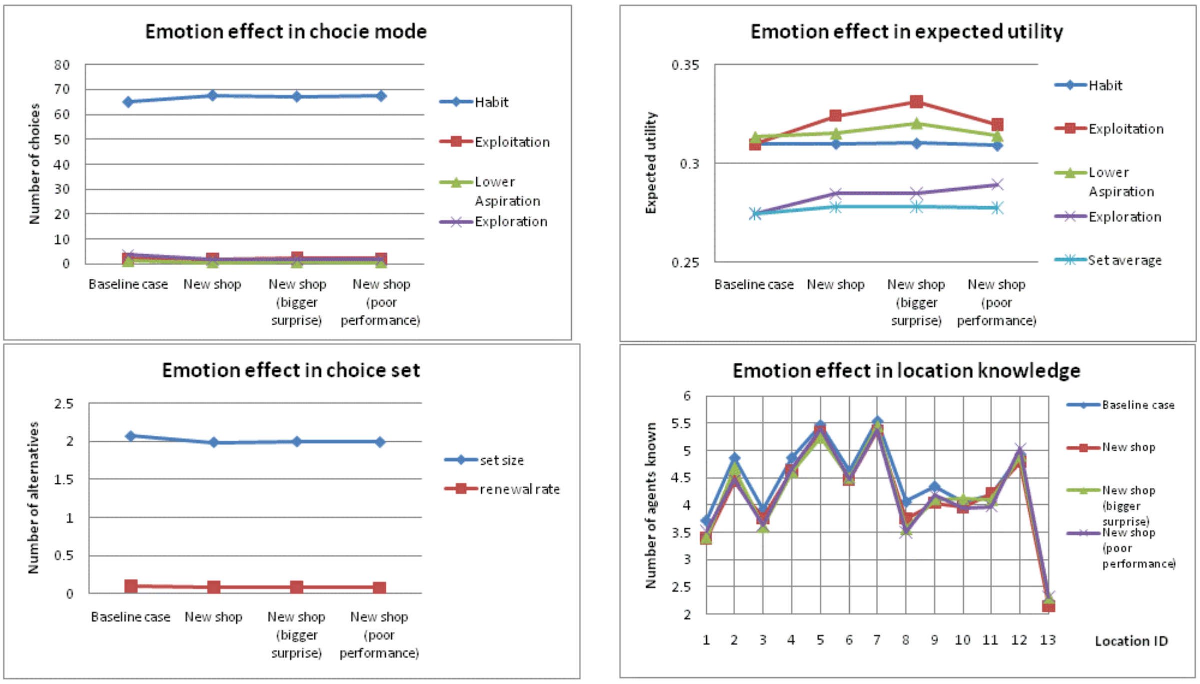

Figure 2 The impact of emotional impact with a new shopping location added

In scenario 4, the newly added shopping location has a poor performance as defined by the negative mean value of the surprises. Comparing scenario 4 with scenario 2, the number of exploitation and exploration choices somewhat increases, while the number of habitual choice slightly decreases. It has the highest expected utility of exploration choices. Given that a negative mean value of the surprises also indicates a higher negative emotional impact, agents that encountered a poor performance may keep it in mind for a longer time and try to avoid it.

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 that of habitual choices. The expected utility of exploration choices is not heavily affected by the parameter settings of affective responses because the probability of discovering particular alternatives is not associated with emotional impact.

Even under the very basic conditions considered here, the emerging patterns in the behavior of the agent-based system are already quite complex. These emerging effects reflect the relatively unique responses which can all be attributed to the proposed parameters of the model. As it shows, the model is capable of incorporating affective response and cognitive learning in addition to habitual choice, exploitation choice and exploration choice. It provides a modeling approach for simulating habit formation and affective responses in location choice dynamics.

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 the 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 choice 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.

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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