Multidimensional Travel Decision-Making: Descriptive Behavioral Theory and Agent-Based Models

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Structured Abstract

Purpose: This chapter explores a descriptive theory of multidimensional travel behavior, estimation of quantitative models, and demonstration in an agent-based microsimulation.

Theory: A descriptive theory on multidimensional travel behavior is conceptualized. It theorizes multidimensional knowledge updating, search start/stopping criteria, and search/decision heuristics. These components are formulated or empirically modeled and integrated in a unified and coherent approach.

Findings: The theory is supported by empirical observations and the derived quantitative models are tested by an agent-based simulation on a demonstration network.

Originality and Value: Based on artificially intelligent agents, learning and search theory, and bounded rationality, this chapter makes an effort to embed a sound theoretical foundation for the computational process approach and agent-based microsimulations. A pertinent new theory is proposed with experimental observations and estimations to demonstrate agents with systematic deviations from the rationality paradigm. Procedural and multidimensional decision-making are modeled. The numerical experiment highlights the capabilities of the proposed theory in estimating rich behavioral dynamics.

1. Background

The study of travel demand estimation, forecasting, and adjustment has long been a vital topic in the field of transportation planning. Being an induced demand, travel demand is often regarded as the product of other activities. Individuals commute to work, drop-off family members, travel for leisure, fly to customers/suppliers, visit relatives/friends, and so forth. While these activities are often differentiated by locations and time, how these spatial/temporal details can be accounted for becomes an essential question for transportation planners and researchers. Moreover, these activities encompass interrelated travel decisions including destination, mode, departure time, and route. Therefore, the complexity arising from the mutual effects of these multidimensional decisions upon each other and from their decision timing needs to be represented.

Traditional travel demand modeling structure distinguishes four decision dimensions: deciding the frequency of travel, choosing a destination, selecting a travel mode, and traveling via a route. These decision dimensions are assumed to follow a predefined sequential manner of trip generation, trip distribution, modal split, and traffic assignment, as known as the "Four-Step" method. Travel behavior research gradually moved from aggregate demand models to more disaggregate individual-level and activity-based models (Bhat and Koppelman 1999; Bowman and Ben-Akiva 2001; Vovsha *et al*., 2008; Zhang et al., 2012; Xiong and Zhang, 2013b). While the majority of interest focuses on advancing single-dimensional (single-facet) choices and more advanced representation of activity pattern such as scheduling (Golledge *et al*., 1994; Bowman and Ben-Akiva 2001), land use influence (Salvini and Miller 2005), and location choices (Bhat and Guo 2007), the linkages among different travel behavioral dimensions are largely ignored (Pinjari *et al*., 2011) and individuals' embedded behavioral processes that influence them to change certain dimension(s) of their travel behavior remain unexploited.

Besides the rigid sequential assumption, travel demand models also rely on other simple and sometimes unrealistic behavioral assumptions in order to keep themselves analytically tractable. Perfect rationality theory is one of the well-known assumptions that individuals are fully rational, have perfect information, and always maximize utility (von Neumann and Morgenstern 1947; Savage 1954). Being an approach with rich results, mathematical rigor, and interesting applications, perfect rationality and utility maximization allow structural insights and explain similarities and differences in travel behavior. However, if using this theory to calculate how certain variations in the situation are predicted to affect travel behavior, "*these calculations obviously do not reflect or usefully model the adaptive process by which subjects have themselves arrived at the decision rules they use*" (Lucas 1986).

The opposite holds true for the computational process models, a group of new methods that depart from rationality assumptions and implement learning, adaptations, information acquisition, and decision making efficiently by taking the advantages of computer power. These models are microsimulations relying on heuristic arguments and imitation of human behavior. A large number of real-world or benchmark problems can be analyzed by applying these models to simulate numerical results in different set-ups. Examples on the rapidly growing list include Pendyala *et al*., (1998), Arentze and Timmermans (2004), Wahba and Shalaby (2011), and Auld and Mohammadian (2010).

On one hand, these models introduce more complex learning, adaptation, and behavioral rules instead of utility maximization. But on the other hand, multi-agent simulation cannot prove but only suggests a certain feature of travel pattern and still assumes sequential decision process. Thus it requires additional theories to conceptualize the more rigorous behavioral foundation and better explain behavior adjustments along multiple choice dimensions (see Arentze *et al*., 2004; Pinjari *et al*., 2011).

Urged by the abovementioned theoretical and modeling issues, this chapter describes an alternative framework to modeling multidimensional aspects of travel behavior. Descriptive theory and models are built upon economics and travel behavior research on learning (Golledge *et al*., 1994; Arentze and Timmermans, 2005), search theory (Stigler 1961), and bounded rationality (Simon 1955; Mahmassani and Chang 1987). The theory recognizes that there are inconveniences and risks associated with each behavior adjustment dimension, which is conceptualized as a search cost unique to each individual and each behavior dimension. On the other hand, an individual, based on his/her spatial knowledge, personal travel experiences, and beliefs, forms subjective expectations on potential gains (search gain) from behavioral adjustments along each behavioral dimension. It is the interplay of these search gains and search costs along all feasible behavioral adjustment dimensions that collectively determine when individuals start seeking behavior changes, how they initially change behavior, how they switch behavior adjustment dimensions, and when they are satisfied and stop changing behavior. The theorization of multidimensional knowledge updating, search model, and behavior process becomes a unified and coherent approach that models the activity and travel decision-making with a consistent behavioral foundation and increased rigor. The theory is supported by empirical observations and the derived quantitative models are tested by agent-based simulation on a demonstration network. For improved readability, emphasis is given to modeling knowledge and multidimensional search. Certain details about search rules and decision rules are excluded. Readers interested in these topics are referred to appropriate references.

2. Theory and Models

The multidimensional travel decision-making theory is conceptualized in Fig. 1. The theory starts with the definition of artificially intelligent agents and their characteristics. Each agent i is treated differently with socio-demographic attributes, personal experience, knowledge, and subjective beliefs. At any given time, an agent has a certain level of knowledge about places, activities, and transport networks in an urban area. This spatial/temporal knowledge can be employed to solve various spatial/temporal decision tasks such as choosing destination, departure time, and routes. This problem-solving process consists of several procedural steps in the true behavioral sense. Firstly, each agent i at a given time period t possesses experiences, denoted as $\mathbf{E}_{it}$. Agents acquire $\mathbf{E}_{it}$ through past searches or through information sources such as internet, media, advanced traffic information system (ATIS), etc. $\mathbf{E}_{it}$ is time-variant as the agent searches and accumulates a-priori experiences in the urban transportation network day-by-day. Travel experiences with similar payoffs that occur routinely may reinforce the agent's memory, while the travel experiences that are not representative may be easily forgotten (Arentze and Timmermans, 2003). Moreover, agents are assumed to be able to search information about one behavioral adjustment dimension at a time, e.g. agents may search for an alternative route or search for an alternative travel mode. Thus each past experience can be mapped into one single dimension d and form a multidimensional memory space $\mathbf{M}^d$.

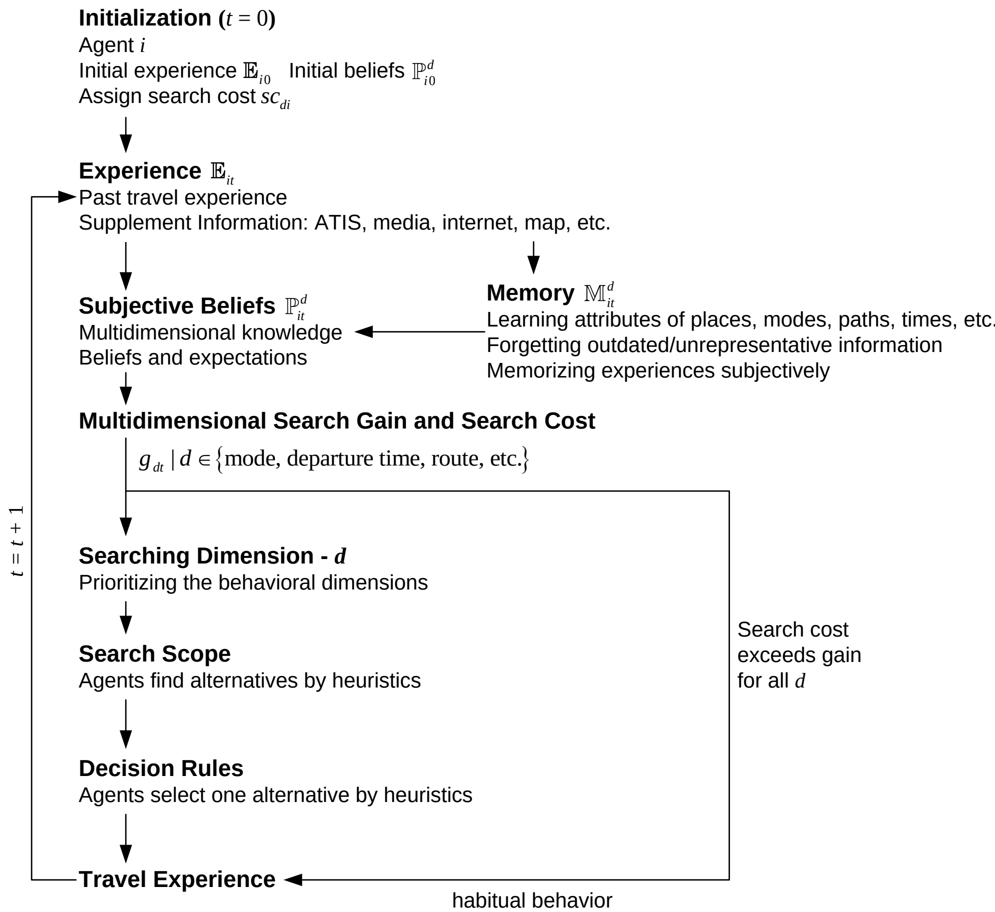


Figure 1. Conceptualization of multidimensional travel decision-making theory

The memory space keeps updating, alters the aspiration level, and changes subjective beliefs $\mathbf{P}_{it}^d$. An agent thus determines the expected gain g_{dt} from a search for alternatives in each behavioral dimension d based on his/her subjective beliefs. Information acquisition and other mental efforts are explicitly modeled as perceived search cost sc_{di} when agents are searching for alternatives for each behavioral dimension. These search cost variables are recognized in this theory as inconveniences and risks associated with each behavior adjustment dimension. It is the interplay of these subjective search gains and costs that jointly determines when a search for alternatives in dimension d is initiated or stopped in time period t. Although the subjective search gain is defined by individual's beliefs and therefore can be quantitatively derived, it is much more difficult to theoretically determine the magnitude of perceived search cost which should be individually different. Once the multidimensional behavioral adjustment evidences can be observed, the perceived search cost and its relations with other variables can be empirically derived.

If an agent decides not to search in a dimension, habitual behavior in that dimension is executed. Otherwise, the agent will employ a set of search rules to search from her/his knowledge and identify a new alternative. After identifying an alternative, she/he needs to determine whether or not to switch to that alternative. The decision rules constitute a mapping from spatial/temporal knowledge (especially experienced travel conditions corresponding to different alternatives) to a binary decision: switch to the alternative or retain habit. Both the search rules and the decision rules should be empirically estimated from observed search processes.

2.1. Modeling Imperfect Knowledge

Search, learning, and knowledge play a crucial role in making a decision. A rational person will choose the best alternative from the set of feasible alternatives. The term "rationality" would also require that this rational person holds the knowledge that is derived from coherent inferences. In contrast, more realistic models are intended to allow modelers to construct agents who systematically do not possess perfect knowledge and do not make correct inferences but make biased ones.

An agent explores decision opportunities by searching her/his feasible environment and learns knowledge about various payoffs related to the search and decisions. Here the spatial/temporal knowledge is generalized as multidimensional vectors with each vector corresponding to a particular dimension. Assume that each agent i at any given time period t possesses a list of past experiences, $\mathbf{E}_{it}$. Each experience is characterized by a generalized cost:

$$C_E = \sum_n \lambda_n \psi_n \tag{1}$$

where n denotes the index of different related attributes such as travel time, cost, schedule delays, mode comfort, etc. ψ denotes the vector of attributes; λ denotes the coefficient to translate values into monetary costs (e.g. value of time). This generalized cost is adopted to measure the outcome of each experience and to set an anchoring point for the search model. Assuming that in each behavioral dimension d, an individual's perceptual capabilities allow the separation of generalized cost into a number of categories. If C_E that falls into the generalized-cost category j has been observed m_j times in prior experiences, the memory this individual has about the generalized cost in dimension d is fully described by a vector $\mathbf{M}^d = (m_1, ..., m_j, ..., m_J)$. Individuals update memory space through learning and forgetting processes. Bayesian learning relies on the premise of some prior knowledge. When new information from various sources becomes available, learning occurs and obeys the Bayes' rule. Forgetting relies on the cognitive weighting of each past experience, which can be measured as a function of the recentness and representativeness of the experience (Arentze and Timmermans, 2003). Once the weight is lower than a certain threshold parameter, the experience will be eliminated from $\mathbf{E}_{it.}$

Bayesian learning theory relies on the premise of some prior memory ($\tilde{M}$). When new evidence (e) from various information sources is available, learning occurs and follows Bayes theorem. That is: the posterior memory is updated using conditional probabilities: $P\left(\tilde{M} \mid e\right) = P\left(e \mid \tilde{M}\right) \cdot P\left(\tilde{M}\right) / P(e)$ (this equation can also be expressed as *posterior = likelihood · prior / evidence*). When a new alternative in this dimension is experienced and the associated generalized cost falls into category j, the updated memory becomes $\mathbf{M}^d = (m_1, \ldots, m_j+1, \ldots, m_J)$. Let the vector $\mathbf{P}^d = (p_1, \ldots, p_j, \ldots, p_J)$ represent an individual's subjective beliefs, where p_j is the subjective probability that an additional search in dimension d would lead to an alternative with jth level of generalized cost. In order to quantitatively link $\mathbf{M}^d$ and $\mathbf{P}^d$, we assume that individuals' prior beliefs and memory follow a Dirichlet distribution, which is a J-parameter distribution. Therefore the posterior beliefs will also be Dirichlet distributed since the Dirichlet is the conjugate prior of the multinomial distribution (Rothschild, 1974). The probability density function is defined as:

$$P = \frac{\Gamma(N)}{\prod_{j=1}^{J} \Gamma(m_j)} \prod_{j=1}^{J} p_j^{m_j - 1} \tag{2}$$

where N denotes the total number of $\mathbf{M}^d$ observations and Gamma function $\Gamma(m_j) = (m_j - 1)!$. According to the law of large numbers, as sample size N grows, this assumption asymptotically converges to:

$$\mathrm{E}(p_j) = \frac{m_j}{N} \tag{3}$$

Bayesian learning is capable of describing updates of spatial knowledge about the attributes of spatial objects, and relations between spatial objectives when repeated observations are available. Travel time on a roadway section, waiting time at a transit station, level of congestion for a specific trip during a peak hour, attractiveness of housing unit in a neighborhood, distance between an origin and a destination, closeness of a shopping center to the route from work back home, etc.

2.2. Modeling Multidimensional Search

An individual, based on her/his past experience $\mathbf{E}_{it}$ and subjective beliefs $\mathbf{P}_{it}^d$, forms expectations on potential gain (search gain) from behavioral adjustments along each dimension. The decision to search for a new alternative is based on the interplay of subjective search gain and perceived search cost. Let an agent's generalized cost on the currently used alternative be C. The subjective search gain (g_{dt}) is based on subjective beliefs, $\mathbf{P}_{it}^d$, and defined as the expected improvement in regard to generalized cost savings per trip from an additional search:

$$g_{dt} = \sum_{j(\forall C_j < C)} p_j \cdot (C - C_j) \tag{4}$$

where C is actually the minimum of all experienced generalized costs because individuals can select from all tried alternatives in dimension d and pick the one with the lowest costs $C_{\min}^d$. We assume all individuals start with a preferred travel pattern. It can be the stabilized travel pattern with an initial generalized cost C_0. Once a policy/congestion stimulus emerges, travel condition deteriorates. Let us further assume that individuals have the initial beliefs that search and switching to another alternative will lead to a travel condition as good as their original travel condition C_0 until they search and experience otherwise. As the search process proceeds, the subjective probability of finding an alternative with C_0 after N searches is 1 / (N+1). Therefore, Eq. (4) can be further simplified as:

$$g_{dt} = \frac{C_{\min}^{d} - C_0}{N+1} \tag{5}$$

While C_0 remains universal among all dimensions, $C_{\min}^{d}$, the currently best travel option(s) in dimension *d*, can differ in each dimension *d* since the search processes in different dimensions vary and result in diverse outcomes. The subjective search gain g_{dt} evolves and reflects how much value each search can gain based on subjective beliefs. Once g_{dt} is less than or equal to zero, it indicates that search along dimension *d* is no longer worthwhile and the search process will not initiate. A positive g_{dt} will asymptotically decrease to zero as the number of searches increases and as a better alternative is found ($C_{\min}^{d}$ getting increasingly closer to C_0).

Furthermore, the theory formulates satisficing behavior that even with positive gains, individuals may stop search once the gain is lower than the perceived search cost. The search and information acquisition are no longer free as this theory recognizes the inconveniences and risks associated with each behavior adjustment dimension. This impedance is conceptualized as a search cost for each agent and each dimension. Search cost can be perceived and inferred once individuals' searching sequence can be reconstructed using empirical observations collected from survey. The empirical data provides evidence about agents' search and decision processes. Each individual follows her/his own path along the three dimensions in reaching the final behavior decisions. When it is observed that an individual ends her/his search in dimension *d* and has searched *N* times along that dimension for the time being, it infers that the individual satisfices after *N* rounds of search in *d*. The search cost must be lower than $g_{d,t-1}$ so that the *N*th search is meaningful and rewarding. Meanwhile, the search cost must be higher than g_{dt} so that the (*N+1*)th search does not occur. Let us denote individual *i*'s search cost along dimension *d* as sc_{di}, which is viewed as an innate personal characteristic for individual *i*. It can be estimated by using the lower and upper bounds:

$$sc_{di} \le g_{d,t-1} = \frac{C_{\min,t-1}^{d} - C_0}{N} \tag{6-1}$$

$$sc_{di} \ge g_{dt} = \frac{C_{\min,t}^{d} - C_0}{N+1} \tag{6-2}$$

$$\overline{sc}_{di} = \frac{1}{2}\left(g_{d,t-1} + g_{dt}\right) \tag{6-3}$$

Note that for each individual, only one of the multidimensional perceived search costs can be perceived from the empirical data. A subsequent regression analysis for all survey subjects and all dimensions thus needs to be estimated in order to empirically model search cost. We specify that the search cost model in dimension *d* as:

$$\begin{aligned} sc_{di} = \beta_0 + \beta_1 C_0 + \beta_2 \text{gender} + \beta_3 \text{fixedsch} + \beta_4 \text{purpose} + \beta_5 \text{income1} + \\ \beta_6 \text{income2} + \beta_7 \text{income3} + \beta_8 \text{distance} + \beta_9 \text{peak} + \beta_{10} \text{veh} + \varepsilon_i \end{aligned} \tag{7}$$

where C_0 is the generalized cost for the originally reported travel experience; distance measures the mileage that the subject travels; Dummy variables include gender (equals to 1 if the subject is female), fixedsch (equals to 1 if the subject has fixed travel schedule), purpose (equals to 1 if the trip purpose is work/school), peak (equals to 1 if the travel is in peak-hour periods), and veh (equals to 1 if household number of vehicles is greater than 2). Different household annual income levels are considered in the model (income1: less than \$50,000; income2: \$50,000 - 100,000; income3: \$100,000 - \$150,000; income4: \$150,000 and above). In our model, C_0 is identified as an instrumental variable (IV) in order to better incorporate the sufficiently high correlation between C_0 and other independent variables. We employ the generalized method of moments (GMM) and two-stage least-squares (2SLS) estimator. Denoting the IV as $\mathbf{z}$ and the independent variables as $\mathbf{x}$, we can estimate parameters $\boldsymbol{\beta}$ from the population moment conditions:

$$\mathrm{E}\left[\mathbf{z}\left(sc_{di}-\mathbf{x}\boldsymbol{\beta}\right)\right]=0 \tag{8}$$

The estimation result is reported in Table 1. The search cost is positively related to the initially experienced generalized cost of the travel. Lower-income agents have higher search costs along the mode dimension. Female agents are more reluctant to search departure times and routes than to search alternative modes. Fixed schedule and traveling during peak-hour increase the search cost for all dimensions. Travel distance has a negative impact on search cost meaning that the longer the travel distance, the more likely she/he will search for alternatives. The coefficients for trip purpose indicate that agents doing commute travels have more incentive to search for alternative modes and departure times. By estimating and applying search cost models, one can make personal/household characteristics endogenous in the search process and model diversified and behaviorally rich multidimensional search. It helps explain why some travelers may adjust routes first while others may adjust departure time first in response to the same stimulus. This feature can potentially provide a rich level of details especially for policy/social equity analysis whence measuring the impacts/benefits by different socio-economic strata of society is of interest.

Table 1. Multidimensional Perceived Search Cost Models (Generalized Method of Moments and Instrumental Variable)

Models:	**Search Cost (*d*: mode)**	**Search Cost (*d*: departure time)**	**Search Cost (*d*: route)**
Variables	Coefficients (std. err.)	Coefficients (std. err.)	Coefficients (std. err.)
Generalized Cost C_0	0.023 (0.010)***	0.008 (0.001)***	0.001 (0.000)***
Gender (female)	0.014 (0.088)	0.162 (0.071)**	0.098 (0.046)***
Fixed schedule	0.118 (0.065)***	0.194 (0.080)**	0.115 (0.045)***
Purpose (work/school)	-0.101 (0.062)*	-0.091 (0.056)*	0.098 (0.048)**
Annual income (< \$50k)	0.188 (0.106)*	-0.272 (0.201)	-0.299 (0.060)***
Annual income (\$50k-\$100k)	0.085 (0.41)**	-0.285 (0.203)	-0.207 (0.066)***
Annual income (\$100k-\$150k)	-0.007 (0.007)	-0.542 (0.234)**	-0.089 (0.086)
Travel distance (10 mi)	-0.020 (0.003)***	-0.008 (0.001)***	-0.006 (0.000)***
Peak-hour travel	0.161 (0.094)*	0.112 (0.062*)	0.010 (0.041)
Number of Cars (> 2)	-0.088 (0.021)***	0.298 (0.092)***	-0.035 (0.053)
Constant	1.341 (0.148)***	0.402 (0.225)*	0.384 (0.068)***

*, **, *** - significant at 90%, 95%, 99% confidence level

It is hypothesized that agents will search the most rewarding dimension with the highest search gain/cost ratio. Successive unrewarding searches along a particular behavioral adjustment dimension (e.g. route) will lead to diminishing subjective search gain for that dimension and at a later point cause the search to shift to a different behavior dimension (e.g. departure time). Once the ratios for all dimensions drop down below one, the multidimensional search process ceases. Since g_{dt} is monotonically decreasing and converges to zero, the search is guaranteed to reach stability. The interplay of these search gains and costs along all feasible behavioral dimensions defines the bounded rationality embedded in the theory. It collectively determines the prospects for profitable searches over finite horizon and guarantees a convergence of behavioral changes. It quantitatively theorizes when individuals start seeking behavioral changes, how they initially change behavior, how they switch behavioral adjustment dimensions, and when they stop the search.

2.3. Search Rules and Decision Rules

An agent will keep the status quo and repeat her/his habitual behavior once she/he decides not to search in any dimension. Once determining a dimension to search, a search process is invoked to find useful alternatives to meet travel demand. Spatial/temporal search is not random and can be biased (Humphreys and Whitelaw 1979). For instance, if a person currently departs at 8 am and is not satisfied with the resulting travel and/or schedule delay, the person may be more likely to try departing at 7:30 am and 8:30 am than 7 am and 9 am (i.e. an anchor effect). Different knowledge extracting technologies can be applied to mine individuals' search rules and decision rules. Here we adopt production rules for shorter-term departure time search and route search. For longer-term travel mode search, the process of identifying an alternative mode is theorized as a hidden Markov process.

The rule-based method was well documented in Arentze and Timmermans (2004). Here we present the hidden Markov method (the main idea is illustrated in Figure 2) which emphasizes the dynamic linkages between time periods.

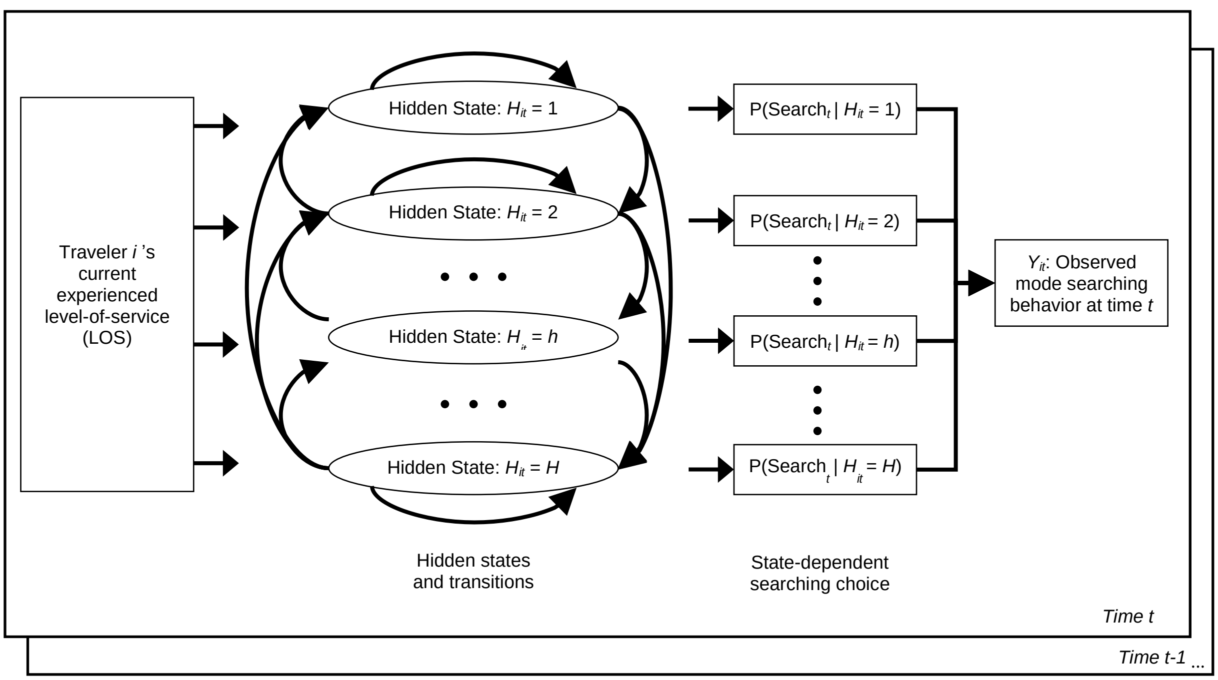


Figure 2. A Hidden Markov Model of Travel Mode Searching Dynamics

As displayed in Figure 2, two major components are highlighted in this model:

- Hidden states and transitions. The transition is triggered by the evolving travel experience. Starting from an initial state distribution (i.e. at time 1, the probability density function $\Pr(H_{i1})$ that traveler i is in state H_{i1}), a sequence of Markov chains is employed to express the likelihood that the level-of-service (LOS) experiences of the habitual mode in the previous periods are strong enough to transition the traveler to another hidden state $\Pr(H_{it} \mid H_{it-1})$. For example, successively experiencing longer waiting time when using transit may cause the traveler to switch to auto-loving state.
- State-dependent decision rules. Given the hidden state that a traveler i is in, the probability that she/he will identify mode y_{it} as the alternative in the mode searching stage at time t is determined by $\Pr(Y_{it} = y_{it} \mid H_{it})$. Y_{it} is the mode searching decision made by traveler i at time t.

An individual's decision probabilities are correlated through the underlying path of the hidden states (y_{i1}, y_{i2}, ..., y_{iN}), because of the Markovian properties of the model. Therefore, the joint likelihood function is given as:

$$\begin{aligned} L\left(H_{it}\right) &= \Pr\left(Y_{i1} = y_{i1}, \cdots, Y_{iN} = y_{iN}\right) \\ &= \sum_{H_{i1}} \sum_{H_{i2}} \cdots \sum_{H_{iN}} \left[\Pr\left(H_{i1}\right) \prod_{t=2}^{N} \Pr\left(H_{it} \mid H_{it-1}\right) \right] \cdot \prod_{t=1}^{N} \Pr\left(Y_{it} = y_{it} \mid H_{it}\right) \end{aligned} \tag{9}$$

More details of this hidden Markov search model regarding model variables and estimation procedure can be found in Xiong and Zhang (2014). After each round of search, a new alternative is identified. Agents either change behavior to use the new alternative or stay with their habitual behavior. This is determined by a set of decision rules. Even though during the multidimensional search process many alternatives may be visited, the final decision is assumed to be the outcome of a series of switching decisions. Production rules derived by various machine learning algorithms (Quinlan 1986; Cendrowska 1987; Cohen 1995) are selected here to represent decision rules. Departing from random utility maximization, this assumption about the search-decision procedure relaxes the unrealistic assumption of human information processing and computational capabilities and incorporates individual-based historical dependencies. It also improves the computational efficiency of agent-based simulation since the execution of production rules only requires minimum computational resources. These search and decision rules are empirically derived for each behavioral dimension and are discussed in greater details elsewhere (Zhang 2007; Xiong and Zhang, 2013ac, 2014).

2.4. Empirical Data Collection

The development of those quantitative models can be data intensive. This research conducts a stated adaptation experiment administered online to explore possible substitutions to the longitudinal information that is typically missing. This survey method is particularly useful when one seeks answers from respondents on a number of what-if questions such as "what would you react if you were faced with specific constraints/conditions" (Arentze *et al*., 2004). It helps capture respondents' multi-faceted behavioral responses. Furthermore, it has the capability to infer the procedural decision-making process which embeds the behavioral foundation of the proposed theory and models since respondents will naturally exhibit satisficing behavior if playing the scenarios repeatedly for a sufficient number of iterations. The survey procedure is reported in Fig. 3.

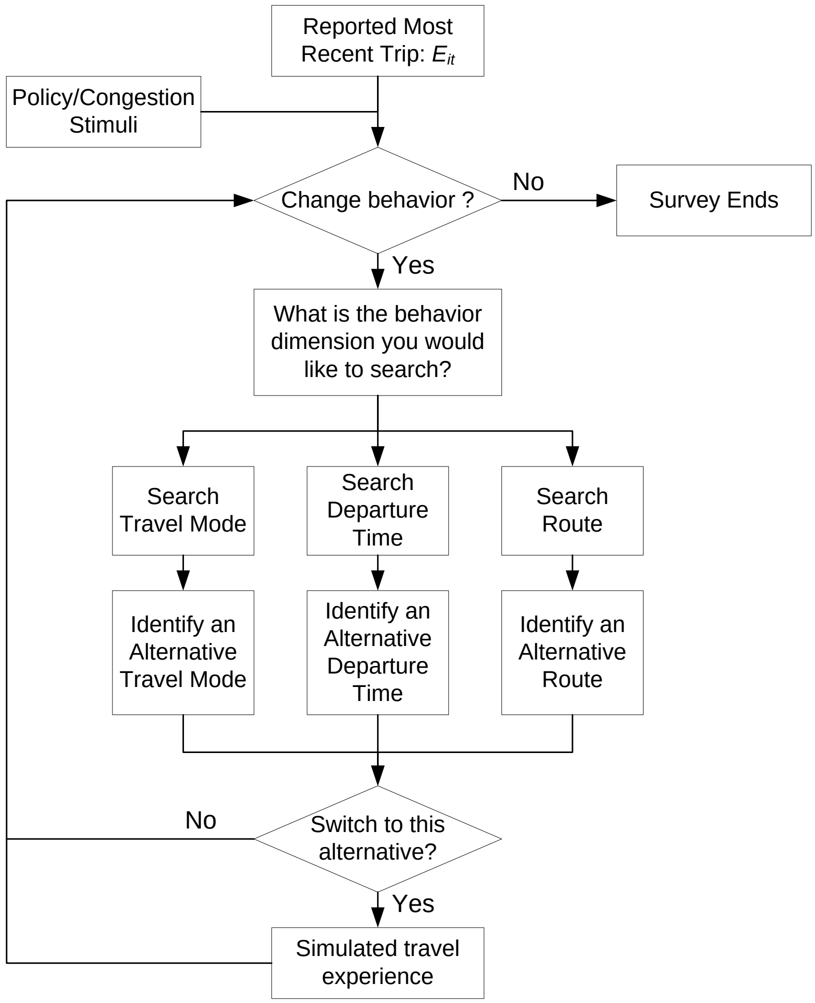


Figure 3. The stated adaptation experiment flowchart

Starting from a self-reported most recent trip, exogenous policy/congestion changes are assumed in each scenario to alter the travel condition for that trip. It is further assumed that each agent will adapt to those changes by searching new modes, departure time, and/or routes. The dimensions wherein the behavior adjustment occurs are asked explicitly in the survey for each subject. The subject then is asked to elaborate the alternative she/he would identify and search along that dimension (this data infers the determination of search rules). Once a search has been recorded by a subject, the program will feed a corresponding travel condition simulated in the back-end for the subject to consider and make a switching decision between the alternative and the habitual one (this data infers the decision rules). Another round of behavior adjustment (could be in the same dimension or in another dimension) will occur unless the subject states satisfactory about the travel experience. Iteratively repeating this process, a complete behavioral adjustment sequence of each subject can be observed. Initial samples include 110 University of Maryland staffs and students. They perform adaptations under schemes such as overall congestion increase and road-pricing scenarios.

3. Simulation Results

The proposed multidimensional behavioral theory and models have been estimated and implemented in an agent-based simulation to demonstrate the capability. A toy network with one origin-destination pair, three alternative routes, and three travel modes (auto, carpool, and transit) is employed. The scenario that is analyzed in this simulation is an assumed 10 percent increase in travel demand which creates excessive travel time and cost for the simulated agents and stimulates them to start the multidimensional behavior adjustments. 90,000 agents are generated in this microsimulation of extended morning peak hours (5:00 am – 10:00 am). Agents' characteristics are synthesized based on Transportation Planning Board (TPB) – Baltimore Metropolitan Council (BMC) Household Travel Survey (2007/2008) data.

In the simulation, agents travel from origin to destination, accumulate experience, make behavioral adjustment on one or multiple dimensions, dynamically update beliefs, and eventually satisfy on their decisions. The uniqueness of the model brings attention to each agent for whom the interplay of search gain and search cost is dynamically modeled in order to determine the behavioral dimension wherein the search and decision process occurs. Fig. 4 illustrates the evolving gain/cost ratio for a particular agent.

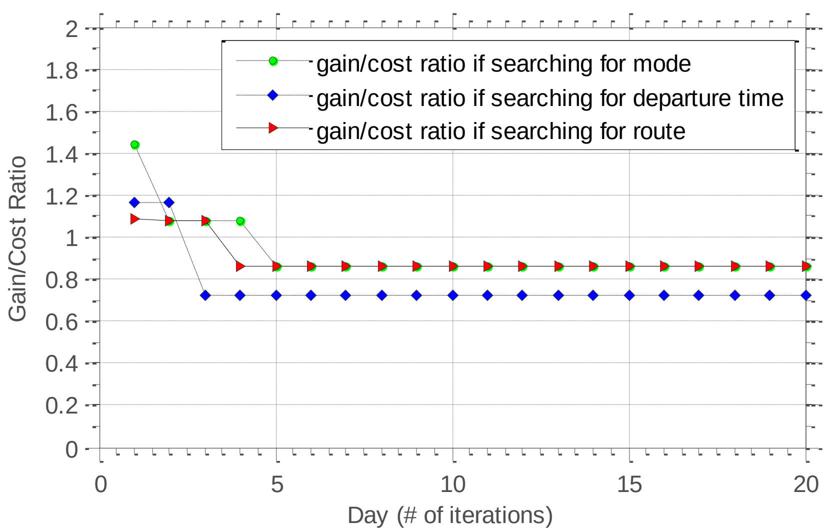


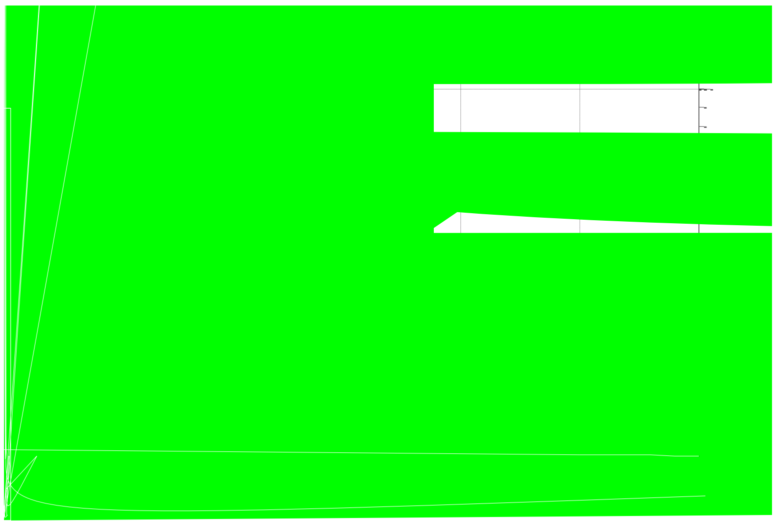
Figure 4. The Evolving Gain/Cost Ratios of Multidimensional Travel Behavior

On simulation day 1, the agent initially believes that all dimensions are rewarding (with all gain/cost ratios above one) while the most profitable dimension is the mode dimension. She/he then employs search rules and decision rules to identify and examine one alternative mode. While the subsequent search reveals further information, this agent's knowledge and subjective beliefs on the mode dimension evolve significantly. And on the second day, the departure time dimension emerges to be the one with the highest gain/cost ratio. A search for alternative departure time is therefore performed. Iterating this process, the agent forms a time-dependent search path about choosing behavioral adjustment dimensions: mode-departure time-route-mode. On the fifth day, the gain/cost ratios of all dimensions drop down below 1, which indicates that this agent subjectively believes that no more searches are necessary. The agent is thus satisfied and stays dormant afterwards. Once a new turbulence emerges in the transport system, such as new policies and booming travel demand, the agent may be influenced in the way that the gain/cost ratios in certain dimensions grow. And the agent may seek further changes.

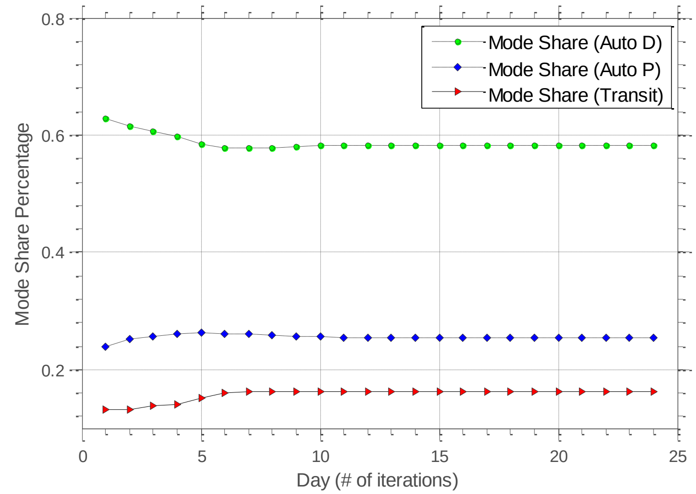
The convergence of the multidimensional behavior is illustrated in Fig. 5(a). Overall, the model predicts active and reasonable agent behavior along the three behavioral dimensions. The convergence processes are smooth. With the innate bounded rationality and satisficing behavior, agents reach steady state and stop search within 25 search iterations. If each agent travels five days a week and all agents start search at the same time, it would take five weeks for the traffic to stabilize and equilibrate on the network. This is an interesting finding that on one hand, it allows us to model the gradual behavior adaptation to exogenous policies (e.g. pricing policy in Stockholm gradually nudge drivers to change behavior, Borjesson *et al*., 2012). On the other hand, it suggests potential applicability of the proposed theory in large-scale planning models and simulation since it embeds multidimensional behavioral responses while maintaining a reasonable converging speed.

In response to the assumed demand increase, changing route and changing departure time are the most significant ways of behavioral adaptation. The initially high route searching frequency cools down rapidly since agents can hardly identify any better alternative routes under the assumed overall demand increase. Agents quickly learn the fact and update the subjective beliefs, which results in a decreasing search gain in the route dimension. Then agents turn to search alternative modes and departure times instead. Thus we can observe in the simulation an increasing number of agents searching for alternative departure times in the second and third simulation days. A few agents search for alternative modes. Agents' mode searching and switching behavior is illustrated in Fig. 5(b). Agents' departure time changes are illustrated in Fig. 5(c).

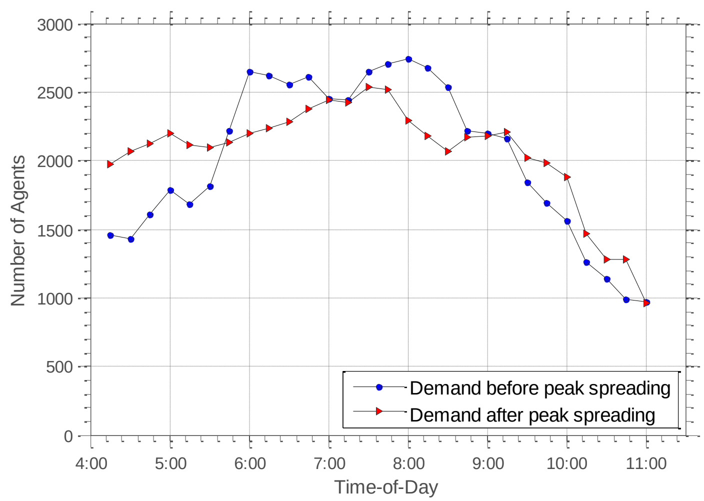
By aggregating the individual behavior into travel patterns, we can observe that the multidimensional learning and adaptation leads to a slight percentage decrease of auto drivers (Auto D in Fig. 5b). Those agents switch to auto passengers (Auto P) or transit users. The aggregate mode share of auto drivers drops from 63.4% to 58.3%. After 6 simulation days, the mode share tends to be stabilized even though from the microscopic level, there still exist some 3,000 travelers changing their travel modes. The active departure time changes lead to a significant peak spreading effect. The assumed demand increase results in more severe congestion and travel time unreliability especially during peak hours. The excessive travel time, cost, and schedule delays make the departure time adjustments necessary in order for the agents to gain an acceptable payoff through search. The model predicts that the dominating behavioral responses to the stimulus are route changes and departure time changes, which are in consistency with the existing research (e.g. Arentze *et al*., 2004). Meanwhile, the model predicts the behavioral dynamics and adaptive processes, which advance our current understanding about multidimensional travel behavior adjustments.



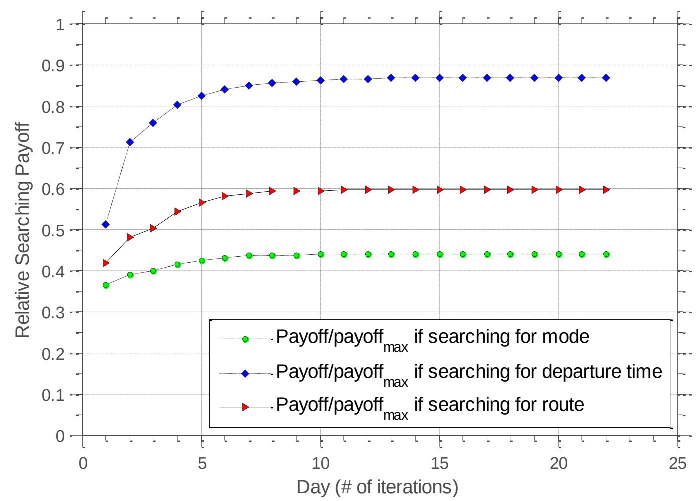
a. The convergence of the multidimensional behavior



b. Agents' mode search and switching behavior



c. Agents' departure time chagnes and peak spreading



d. Agents' payoff dynamics

Figure 4. Agent-based experiment of the multidimensional travel behavior theory

Travelers in the multidimensional agent-based model are not perfectly "rational" in that they do not maximize their utility (or payoff). Instead, they are restrained by information acquisition cost, decision cost, computational limitation, time budget, and deadlines. They are not perfectly rational also in the way that they follow different intuitives and heuristic behavioral rules. Fig. 5(d) demonstrates that through multidimensional learning and adaptation, agents search and improve their relative searching payoff. This term is defined as the ratio of the cumulative actual search gain and the cumulative subjective search gain (i.e. subjectively believed maximum payoff from the search) for all the searchers. Judging by the curves, the departure time dimension turns out to be the most profitable dimension. Once searching in this dimension, agents are able to retrieve the highest relative searching payoff. However, this learning and adaptation does not ensure them to make decisions that result in maximum payoff. This example demonstrates the bounded rationality of the agents in search and changing their behavior.

4. Discussion and Conclusion

This chapter introduces a theoretical framework to modeling multidimensional travel behavior based on artificially intelligent agents, search theory, and bounded rationality. For decades, despite the number of heuristic explanations for different results, the fact that "*almost no mathematical theory exists which explains the results of the simulations*" (Herbert 1999) remains as one of the largest drawbacks of agent-based computational process approach. This is partly the side effect of its special feature that "no analytical functions are required". Among the rapidly growing literature devoted to the departure from rational behavior assumptions, this theoretical framework makes aen effort to embed a sound theoretical foundation for computational process approach and agent-based microsimulations. The theoretical contributions are three-fold:

- A pertinent new theory of choices with experimental observations and estimations to demonstrate agents with systematic deviations from the rationality paradigm. Modeling components including knowledge, limited memory, learning, and subjective beliefs are proposed and empirically estimated to construct adaptive agents with limited capabilities to remember, learn, evolve, and gain higher payoffs. All agent-based models are based on empirical observations collected via various data collection efforts.
- Modeling procedural and multidimensional agent-based decision-making. Individuals choose departure time, mode, and/or route for their travel. Individuals also choose how and when to make those choices. A behaviorally sound modeling framework should focus on modeling the procedural decision-making processes. This study seeks answers to questions that largely remain unanswered including but not limited to: (1) When do individuals start seeking behavior changes? (2) How do they initially change behavior? (3) How do they switch behavior adjustment dimensions? (4) When do they stop making changes?
- The transformation from the static user equilibrium to a dynamic behavioral equilibrium. Traditional solution concepts are based on an implicit assumption that agents have complete information and are aware of the prevailing user equilibrium. However, a more realistic behavioral assumption is that individuals

have to make inferences. These inferences can be their subjectively believed search gain (or perceived distributions of travel time and travel cost), the multidimensional alternatives they subjectively identify, and the heuristics they employ to evaluate alternatives. It is the process of making inferences that occupies each individual in making a decision. With search start/stop criteria explicitly specified, this process should eventually lead to a steady state that is structurally different to user equilibrium.

The estimation of the proposed agent-based models usually needs additional behavior process data. Whether or not the increased data needs can be justified by improved model realism and model performance in applications can be a subject for further examination. This chapter empirically estimates the models using data collected from a stated adaptation survey, a similar but different survey structure compared to stated preference experiments. This survey method effectively captures adaptations in response to changing attributes or context and can record behavior process if implemented in an iterative manner (see e.g. Khademi *et al.*, 2012). The observed behavior process actually is a search path possessed by each respondent. This historical information can be applied to further calibrate the knowledge model or the search cost models. Another future research direction may explore how advanced data collection technologies such as GPS-surveys, smartphone applications, and social network data can improve the affordability and quality of behavior process data and further support the proposed modeling framework.

The numerical example presented in the paper highlights the capabilities of the proposed theory and models in estimating rich behavioral dynamics, such as multidimensional behavioral responses, day-to-day evolution of travel patterns, and individual-level learning, search, and decision-making processes. The computational efficiency of the proposed models needs further exploration through real-world implementations using agent-based simulation techniques. It is believed that the flexible framework, computational efficiency, and more realistic assumptions can make the proposed modeling tool extremely suitable for integrated large-scale multimodal planning/operations studies which typically have to cope with millions of agents. This work is primarily exploratory in its conceptualization of a descriptive theory, estimation of quantitative models, and demonstration in an agent-based microsimulation. In an era of big-data access, multi-core processors, and cloud computing, the ambition of transportation demand modelers has never been greater. The hope is that the preliminary findings in this chapter could raise interest in the behavioral foundation of multidimensional travel behavior as well as in microsimulating people’s complex travel patterns in the time-space continuum. Extensive examination of the proposed tool on a larger and more representative survey sample and for real-world studies is necessary before we can conclude that the tool is fully practice-ready.

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