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Analysis of park-and-ride decision behavior based on Decision Field Theory

Huanmei Qin [a,*], Hongzhi Guan [a], Yao-Jan Wu [b]

[a] Key Laboratory of Traffic Engineering, Beijing University of Technology, Beijing, China
[b] Department of Civil Engineering, Parks College of Engineering, Aviation and Technology, Saint Louis University, St. Louis, USA

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ABSTRACT

Park and ride is a kind of traffic management solution to the traffic congestion problem in urban cities. This paper analyzes the decision making behavior of *Park and Ride* from a psychological point of view. Decision Field Theory is used to establish the decision model of *Park and Ride*. The proposed decision model is calibrated using real-life experimental survey data and has proved to be able to account for the complex decision behavior processes observed in the experimental survey data. The model demonstrates the psychological decision processes of individual travelers and the decision characteristics, such as simple decision, indecision and preference reversal. The effects of factors, e.g. deliberation time, deliberation threshold and initial preference, for mode choice are also examined. The proposed model demonstrates its capability of analyzing park-and-ride decision behavior and providing policy makers with useful information for future promotion and planning for park-and-ride facilities.

1. Introduction

Due to rapid development of cities around the world, the rapid increase of vehicles, traffic congestion, traffic safety and environmental pollution are becoming serious issues. Transit has been promoted in many cities around the world to facilitate people's travel. *Park and Ride* is regarded as a new travel mode that attracts more private car owners to use transit. Its function is inducing the car drivers to park there and then take public transportation to city centers by providing low or free transferred parking fees for cars. This will relieve the traffic pressure in city center or congestion area. Some cities, such as Fairfax (Washington, DC), and St. Louis in the US and Oxford in the UK, have built many park-and-ride facilities and have proved successful. Currently, park-and-ride facilities are in the beginning stages in China. For example, Beijing and Shanghai conducted pilot studies on the feasibility of park-and-ride facilities. However, little research has been done on how to attract the car travelers to choose the mode of *Park and Ride*. Therefore, analyzing the decision behavior mechanism for *Park and Ride* from a psychological point of view will be beneficial for transportation policy makers to understand the *Park and Ride* decision behavior and formulate traffic policies.

For human beings, decision making is a complex process with two fundamental characteristics: deterministic versus probabilistic and static versus dynamic. Deterministic theories assume a binary (true or false) preference relation for any pair of options. Probabilistic theories assume each pair of options are mapped into the closed interval [0, 1] using a probability function (Busemeyer & Townsend, 1993). Static theories assume that the length of deliberation time is independent of the

* Corresponding author. Address: Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology, China. Tel.: +86 10 6739 6062; fax: +86 10 6739 1509.
E-mail address: hmqin@bjut.edu.cn (H. Qin).

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preference relation (the probability function), while dynamic theories assume the preference relation (the probability function) changes as a function of deliberation time (Busemeyer & Townsend, 1993).

Recent research regarding park-and-ride decision behavior mainly used the static random utility theory. For example, Xiong and Yang (2008) conducted a stated preference survey for park-and-ride choice behavior in large events and established a park-and-ride choice model by a disaggregated Logit model. The relevant countermeasures to improve the service of park-and-ride facilities were also presented according to the model estimation. He, Wang, and Chen (2009) established a binary Logit model using the stated preference survey data in Nanjing, China. The results show that income, driving experience, trip purpose, traffic congestion level, and parking fees have significant impacts on the use of the park-and-ride facilities. Huang and Zhou (2007) developed a Probit-based stochastic equilibrium model considering the significant errors produced by the independent and irrelevant hypothesis of Logit. The park-and-ride choice behavior is analyzed by a numerical solution algorithm. Arne (2004) developed four different Logit models using stated choice data to forecast the demand for an employee park-and-ride service. These models showed that the drivers with low income, more cars, lack of parking spots at destination have high tendency to utilize park-and-ride facilities. Molin and Bos (2009) established the latent class models to explore heterogeneity among car drivers with respect to park-and-ride preferences. The models were estimated from data observed in a stated choice experiment that included the choices of park and ride, car and public transportation alternatives. Their results showed that the push policy measures are likely to be more effective in increasing park-and-ride utilization compared to the pull policy measures.

The above research on park-and-ride choice behavior is mainly based on economic theories. It is not suitable to analyze the changes of choice behavior in the situation when new options are available. The economic theories are unable to explain the effects of the factors of cognitive capability, deliberation time, and attention on the decision behavior. The random utility theory (McFadden, 1986), one of the economic theories, is regarded as a black box and lacks of a decision process mechanism. Therefore, the dynamic decision theories are more suitable for explaining the motivation and cognitive mechanism.

Decision Field Theory (DFT) is a dynamic, cognitive approach to modeling human decision making based on psychological principles. This approach was initially proposed as a deterministic, dynamic model (Townsend & Busemeyer, 1989). Soon afterwards, the theory was developed as a stochastic, dynamic model of decision making behavior (Busemeyer & Diederich, 2002; Busemeyer & Townsend, 1992). This approach aims to maximize utility and concentrates on the underlying deliberation process with psychological adjustments. This approach can also account for multi-alternative and multi-attribute choice problems and the effects of decision time on speed–accuracy tradeoffs. DFT has also been extended to model rule learning and rule-based decision making.

Several applications of DFT can be found in the clothing industry. Duan and Li (2010) used DFT to compare the degree of clothing style by quantifying human being's complex psychological decision making process. Li (2011) established a decision model of multi-alternative DFT. This model reflects the psychological effects of decision makers while the clothing style is being determined. At present, several applications of DFT can be found in the field of transportation research. Stern (1999) studied drivers' reactions to congestion under time pressure using DFT. Decision rules of lane switching on a congested road are tested at different levels of time pressure. The results showed that people driving under congestion have an increasing use of non-compensatory decision rules and it was also found that exogenous time pressure has effects on both the deliberation process and the use of information. Gao and Wang (2009, 2010) explored the driver's route choice behavior under guidance information based on the combination of DFT and Bayesian theory. The simulation results showed that the unreliability of the information, previous travel experiences, preference for different road alternatives have significant effects on driver route choice behaviors. Johnson and Busemeyer (2005a) applied computational modeling techniques to investigate transitions from deliberative to routine decision making. The computational model, using the Rule-based Decision Field Theory (RDFT), offers a psychologically plausible account of the dynamic behavior. Diederich (2003) introduced the Multi-attribute Decision Field Theory (MDFT) model describing both the dynamic and the stochastic nature of decision making and accounting for the observed changes in choice probabilities, including preference reversals as a function of time limit. Five different time limits were used to test the decision maker on their capability of model prediction.

To authors' best knowledge, few research efforts used DFT to model the decision process for *Park and Ride*. This paper will use DFT to analyze the decision behavior process of three travel modes: *Car*, *Park and Ride*, and *Bus and Subway*. The paper is organized as follows. First, DFT is explained. Next, a custom computer program is developed to collect real-life survey data. The data is used for the modeling process and to verify the proposed DFT model. The verified model will be used to investigate travelers' decision process in several scenarios. Finally, the paper is concluded with model discussion and future work.

2. Decision Field Theory

Decision Field Theory (DFT) is a combination of two prior and independent lines of psychological theory: approach–avoidance theories of motivation and information-processing theories of choice response time (Busemeyer & Townsend, 1993). According to Johnson and Busemeyer (2010), DFT has several basic hypotheses. First, DFT assumes that attention shifts to different dimensions attribute of the choice option over time. Second, the current focus of attention generates a relative evaluation for each choice option. Third, these momentary evaluations are accumulated over time to describe the current preference for each option at each point. This accumulative process can be subject to specific effects such as gradual decay to produce recency effects and inhibitory influences from competing options.

2.1. Connectionist network model of Decision Field Theory

DFT model is based on the connectionist network (Busemeyer, Johnson, & Jessup, 2006, chap. XI; Roe, Busemeyer, & Townsend, 2001). As shown Fig. 1, the network generally has three layers. The first layer computes the weighted utility according to the attributes of different options and attention weights as formulated in

$$U_i(t) = \sum_{j=1}^{n} W_j(t) \cdot m_{ij} + \varepsilon_i(t) \tag{1}$$

where $U_i(t)$ is the weighted utility for option i at time t, m_{ij} is the evaluations for attribute j of option i. $W_j(t)$ is the momentary attention weights linked to attribute j. The average value of the attention weights corresponds to the weight in deterministic utility theory. $\varepsilon_i(t)$ is the error term with a mean of zero, which represents the influence of irrelevant features or features outside of control, and n is the number of attributes for option i.

The outputs of the second layer are valences which represent the advantage or disadvantage being considered for each option at a particular time point. These valences change stochastically over time as the decision maker's attention shifts unpredictably from one attribute to another.

$$v_i(t) = U_i(t) - U_g(t) \tag{2}$$

$$U_g(t) = \sum_{k \neq i} U_k(t)/(m-1) \tag{3}$$

where $v_i(t)$ is the valence for option i. $v_i(t) > 0$ indicates that the option i has an advantage under the current focus of attention while $v_i(t) < 0$ indicates that the option i has a disadvantage under the current focus of attention. $U_g(t)$ is the average utility of the other $(m-1)$ options and m is the number of options.

The third layer is a competitive recursive network. The outputs of this layer are the evolving accumulative preferences for the options at a particular time point. The accumulative preference is formed by the integration of the preference at previous time points and the temporal input valences. The preference state for option i is computed according to the linear dynamic system.

$$P(t+h) = S \cdot P(t) + V(t+h) \tag{4}$$

where $P(t)$ is the preference vector for all options at time t, $V(t)$ is the valence vector for all options at time t, $P(t+h)$ is the preference at time $t+h$, and S is feedback matrix. Eq. (4) can be further expanded as

$$P_i(t+h) = s_{ii} \cdot P_i(t) + \sum_{k \neq i} s_{ik} \cdot P_k(t) + v_i(t+h) \tag{5}$$

where $P_i(t+h)$ is the preference for option i at time $t+h$. s_{ii} is self-feedback coefficient with positive value. $0 < s_{ii} < 1$ suggests decay in the memory or impact of previous valences over time. $s_{ii} > 1$ suggests growth in the memory or impact of previous valences over time (Busemeyer & Johnson, 2008). $s_{ii} = 0$ suggests no impact of previous preference. $s_{ii} = 1$ suggests perfect memory impact of previous preference (Roe et al., 2001). s_{ik} is negative lateral feedback coefficient. $s_{ik} < 0$ generates competition among options. $s_{ik} = 0$ represents independence among options. s_{ik} is postulated to be inversely related to the conceptual distance between the options. The preference state vector, $P(t)$, remains bounded as long as the eigenvalues of S are less than one in magnitude. $P_i(0)$ is the initial preference for option i which represents the past travel experience. h is the decision step size.

Eqs. (6)–(8) are three alternative methods commonly used to calculate s_{ik} (Duan & Li, 2010; Li, 2011).

$$s_{ik} = s_{ki} = 0.042 \cdot \frac{1}{1 + e^{20*(d-2.4)}} \tag{6}$$

$$s_{ik} = s_{ki} = -e^{-d} \tag{7}$$

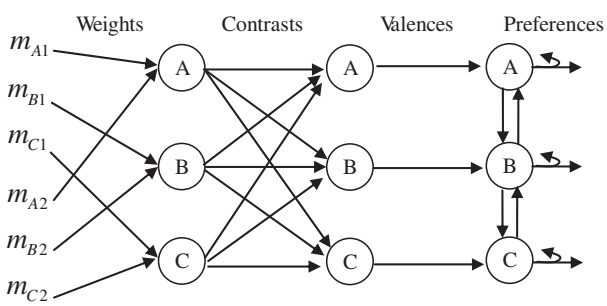


Fig. 1. Connectionist network model of DFT (revised from Roe et al. (2001)).

$$s_{ik} = s_{ki} = -0.10 \cdot e^{-0.022 * d^4} \tag{8}$$

$$d = \sqrt{\sum_{l=1}^{n} (m_{il} - m_{kl})^2} \tag{9}$$

where d is the Euclidean distance.

2.2. Decision stopping criteria

In terms of model application, DFT-based model will not stop running until a criterion is met. DFT-based model has two decision stopping criteria (Roe et al., 2001): time and preference.

The first one is that the option with the maximum preference state is chosen within a fixed time T due to external control. The second one is that, without a time limit, the deliberation process continues until any one of the preference states exceeds a threshold value. The first option exceeding the threshold is chosen. This situation is generally controlled by the decision maker internally (Busemeyer & Diederich, 2002; Ratcliff, 1978).

2.3. Model estimation

The accumulative preference process of DFT can be regarded as a Markov process (Busemeyer & Townsend, 1992; Roe et al., 2001). One of the estimation methods is matrix formulas which need to predefine the drift coefficient and diffusion coefficient. Then, this method can compute the choice probabilities and distribution of choice response times (Busemeyer & Johnson, 2004; Diederich & Busemeyer, 2003; Johnson & Busemeyer, 2005b). The other estimation method is to generate predictions from the model through Monte Carlo computer simulation.

3. Experimental survey

An experimental survey is designed and conducted to not only estimate the parameters in the proposed DFT-based decision behavior model but also verify the usefulness of the proposed model.

3.1. Method

It is difficult to completely and accurately record the psychological decision processes of individuals for the travel mode choice because the decision behavior process of human beings is complex and the experimental technology is limited. The experimental methods regarding the information tracing process are used and modified to design the experiment. These include process tracing technology (Schulte-Mecklenbeck, Kühberger, & Ranyard, 2011) and eye movement tracing technology (Glimcher, 2001; Rayner, 1978).

The basic idea of the process tracing is based on the cognitive information processing theory (Schulte-Mecklenbeck et al., 2011). Process tracing is often utilized to analyze the dynamic decision activity to understand the effect of various psychological factors in decision behavior. One of the process tracing methods is Information Display Board (IDB) (Jacoby, Jaccard, Kuss, Troutman, & Mazursky, 1987; Payne, 1976). IDB uses a 2-D information matrix to collect information from examinees. Typically, the rows are options (alternatives) and columns are attributes for each option. During the experimental process, the specific information for each element of the matrix is invisible at first. The examinee makes a choice by clicking and comparing the attributes information for all alternatives. The information selection and comparison process is recorded and used to analyze the psychological decision process.

The IDB method is selected for this study because of cost-effectiveness and straightforwardness. IDB method is revised and implemented in a custom electronic questionnaire program using Microsoft Visual Studio 2010. The data will be recorded automatically in an Excel file for further analysis.

3.2. Survey interface design and implementation

The electronic questionnaire used to collect data in this study consists of the following data inputs:

Input 1: Fundamental information of the examinees

The information includes sex, age, occupation, income and car ownership.

Input 2: Daily travel information

Two questions regarding daily travel information are asked. The first one is whether the examinee have ever used the park-and-ride facility in the past. The second one is about the initial preferences for the travel modes depending on various

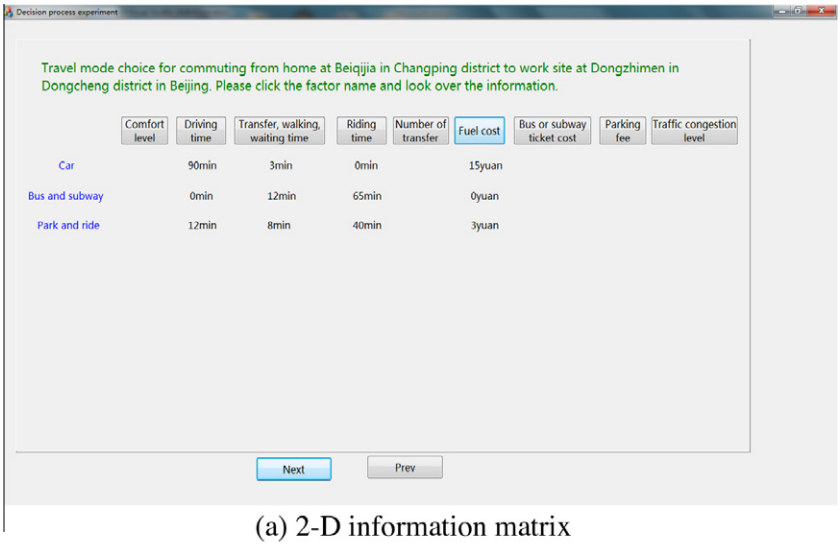
travel purposes. The examinee is required to choose one travel mode among *Car*, *Bus and Subway*, *Park and Ride* and *Others* for each travel purpose. The examinee is also required to respond to this question as quickly as possible based on his/her past travel experience. The questions regarding travel purposes include visiting friends, buying clothes, eating outside, seeing a movie, going to a supermarket, going to a park, going to a bookstore and going to a hospital.

Input 3: Influencing factors in travel mode choice

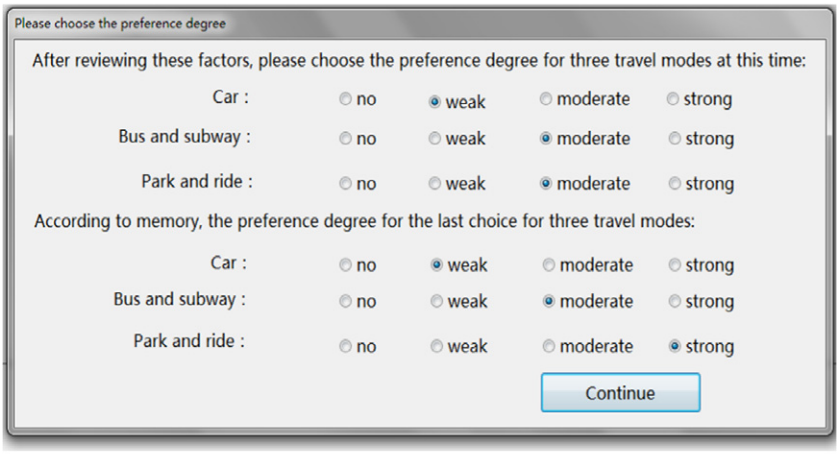
Influencing factors included in this study are driving time, transfer, walking and waiting time, riding time, fuel cost, bus or subway ticket cost, parking fee, comfort, traffic congestion and the number of transfers. All these factors are evaluated in five levels: (1) very unimportant, (2) unimportant, (3) important, (4) relatively important, and (5) very important. Note that the definition of the influencing factor "parking fee" depends on the mode of travel. For *Car*, "parking fee" refers to the cost of parking at the trip destination. For *Park and Ride*, "parking fee" refers to the cost of parking at the park-and-ride facility. For *Bus and Subway*, there is no parking fee.

Input 4: Decision process

A travel decision scenario is created to analyze the examinee's decision process. The home place (Beiqijia in Changping district) and the work place (Dongzhimen in Dongcheng district) in Beijing are marked on a map. To collect the data regarding the examinee's decision process, the interface based on the concept of IDB is developed as shown in Fig. 2. Fig. 2a shows a 2-D information matrix. Each row represents the travel mode (*Car*, *Bus and Subway*, and *Park and Ride*) and each column



(a) 2-D information matrix



(b) the preference degree for three travel modes

Fig. 2. Example of the questionnaire interface.

Table 1
The complete information for three travel modes based on different influencing factors.

	Travel time (min)			Travel cost (yuan)			Comfort level	Traffic congestion level	Number of transfers
	Driving time	Transfer, walking and waiting time	Riding time	Fuel cost	Bus or subway ticket cost	Parking fee			
Car	90	3	0	15	0	8	9	9	0
Bus and Subway	0	12	65	0	4	0	2	2	1
Park and Ride	12	8	40	3	2	2	4	1	1

represents the influencing factors, mentioned in the previous step. The information for each matrix element is invisible by default. Thus, the examinee needs to click the header of each influencing factor one after another to reveal the corresponding information for all travel modes. When the examinee is convinced to make a decision based on the provided information, he/she can click the "next" button and choose one travel mode for further analysis in the study.

Generally, an examinee would click many factors sequentially to review the information before making a final choice. In our design, a dialog box regarding the preference degree for the three travel modes will be displayed after the examinee clicks every two factor headers. The preference degrees the examine can chose are "no intention", "weak", "moderate" and "strong." The examinee can choose one preference degree for each travel mode. There is no limit for deliberation time but the time is recorded for further analysis. In order to obtain the information regarding the memory retention for each examinee in the decision process, the examinee also chooses the preference degree for the last preference choice according to his/her memory when the dialog box is displayed at the second time. Fig. 2b shows an example of the dialog box.

Table 1 shows the complete information revealed to the examinee when the header is clicked on the interface. The values of the influencing factors are defined according to the revealed preference (RP) survey data for *Park and Ride* in Beijing, China in June, 2010 (Qin, Guan, Ao, & Liu, 2012). It should be noted that the comfort level of public transportation and traffic congestion state are categorical variables. The value of comfort level ranges from 1 to 10. 1 represents very uncomfortable while 10 represents very comfortable. The value of traffic congestion level ranges from 1 to 10. 1 represents free-flow traffic level while 10 represents heavily congested level. Note that all the variables are normalized before the model parameter calibration.

3.3. Data collection

The examinees in the experiment have at least one car in their household and have experience in driving cars. It is assumed that these examinees have basic knowledge of the parking fee, fuel cost, etc. and potentially used or will use the park-and-ride facility. The contacts of all potential examinees were first recruited from campus interviews and local networking events. Several phone interviews were conducted to determine if these potential examinees met the requirements of this experiment. Among all potential examinees, 135 people meet the requirements and are willing to participate in the experiment. The experiment was conducted through e-mailing the custom program package to each examinee. To make the examinees familiar with the questionnaire interface, a telephone purchase decision trial was conducted using the similar forms as shown in Fig. 2. Once the examinees were familiar with the interface, each examine was allowed to conduct the decision process trial once. Each questionnaire was finished on their own computer and the result was recorded in a file. All the files were required to be sent back by a designated time.

The experiment was conducted from May to June in 2012 in Beijing. During the experiment, 124 samples are received and the response rate is about 92%. The number of effective samples is 107. Through the investigation analysis, 68% of the examinees are male and 32% of the examinees are female. The majority of examinees (90%) are between 21 and 40 years old. The occupations of the examinees are mainly public servants (10%), public institution personnel (38%) and professional technical personnel (46%). 83% of the examinees have monthly income between 2000 yuan to 10,000 yuan. 92% of the examinees have one car and 8% of them have two cars. Only 13% of examinees have used the park-and-ride facility at least once.

4. Decision behavior model of *Park and Ride*

The parameter estimation is mainly based on the experimental survey data. With the estimated parameters, DFT-based decision behavior model for *Park and Ride* will be established. The dynamic deliberation process predicted by the model will be compared with that by the statistic results of the experimental data to verify the proposed model.

4.1. Model parameter estimation

4.1.1. Weights $W_j(t)$ for the influencing factors

The weights represent the average amount of attention the examinee allocates to each factor. Based on the data collected in Input 3 on the questionnaire, each importance level is assigned a value. "Very unimportant" is assigned the value 1,

"unimportant" is assigned the value 2, "important" is assigned the value 3, "relatively important" is assigned the value 4 and "very important" is assigned the value 5. Each weight value in Table 2 is calculated as the total score of each influencing factor divided by summation of all the scores input by all the examinees. In other words, the summation of all weights in Table 2 should be equal to 1.

4.1.2. Feedback matrix S

The self-feedback coefficient represents the memory retention capability of each examinee during the decision process. In order to estimate this coefficient, the examinees in the experiment need to choose the preference degree for the last preference choice according to his/her memory when the dialog box is displayed at the second time. Fig. 2b shows an example of the dialog box. The choices of the preference degree for three travel modes at the second time are compared with those at the first time. If the before and after choices for the same travel mode are the same, the value is set 1; otherwise 0. The average value of all the questionnaires, 0.915 in our study, is used as the value of the self-feedback coefficient. Hence, $s_{11} = s_{22} = s_{33} = 0.915$.

The lateral feedback coefficient s_{ik} is computed according to the distance among options (travel modes) in the attribute (factor) space. The Eq. (8) is chosen in this study because the prediction error is the smallest compared to Eqs. (6) and (7) based on our experimental data.

4.1.3. Initial preferences $P_i(0)$

The initial preference represents the inclination toward a travel mode. The data regarding the travel mode choices under eight daily trip purposes are used to calibrate the parameter for initial preferences, $P_i(0)$. The data are collected in Input 2 of the questionnaire. The examinee is required to choose one travel mode among *Car*, *Bus and Subway*, *Park and Ride*, and *Others* as quickly as possible under eight daily travel purposes and based on his/her past travel experiences. Among all the examinees, the percentages of choices for *Car*, *Bus and Subway*, *Park and Ride*, and Others are used as the average initial preference. Thus, the initial preferences for *Car*, *Bus and Subway*, *Park and Ride*, *Others* are 66.36%, 26.87%, 1.05% and 5.72%, respectively.

4.1.4. Other parameters

According to previous literature (Gao & Wang, 2009; Roe et al., 2001), the error term $\varepsilon_i(t)$ follows the normal distribution with different means and variances. The decision step size h is generally set as a smaller value. In our study, the error term is assumed normally distributed with a mean of zero and a variance of one. The simulation results show that when the step size h is 1, the output is fairly close to the experimental results.

4.2. Comparisons of the simulation and experimental survey results

The computer simulation method is used in this study to analyze the dynamic process of accumulative preference. The software program developed by Matlab is used to implement the prediction model based on the estimated and predefined parameters in Section 4.2. For each travel mode and deliberation time combination, 20,000 simulation runs are executed.

According to Section 2.2, decision stopping rules, the maximum stopping time T is required to be determined to stop the model. The maximum stopping time T is set to 70 s and the minimum stopping time T is set to 0 s, meaning that the decision maker selects a choice based on his/her initial preference. When the model prediction stops, the option with the maximum preference is chosen. The model prediction results are shown in Fig. 3a. To obtain the choice probability using the experimental survey data, the deliberation times are divided into several time groups: 0–10 s, 10–20 s, etc. The choice probability results for three travel modes are illustrated in Fig. 3b.

As shown in Fig. 3a, the probabilities for *Car* and *Bus and Subway* decrease and those for *Park and Ride* increase as the deliberation time increases. The results are fairly similar to the results from the experimental survey data as shown in Fig. 3b. The results indicate that increasing the deliberation time for decision makers would improve the probability for choosing *Park and Ride*. Therefore, this info is crucial for transportation agencies to develop strategies to attract more travelers to use the park-and-ride facilities. The potential strategy is to provide travelers with additional park-and-ride information, such as travel information regarding facility locations, parking fee, and available parking spots.

The overall average error between the model prediction and the experimental results is 5.8%. The maximum error is −11.6% (the deliberation time = 36.6 s), and the minimum error is 0.2% (the deliberation time = 25.5 s). 82% of the absolute error is below 10%. Therefore, the decision behavior model has proved reliable and the model parameters are appropriately

Table 2
The weights of the influencing factors.

	Travel time (min)			Travel cost (yuan)			Comfort level	Traffic congestion level	Number of transfers
	Driving time	Transfer, walking and waiting time	Riding time	Fuel cost	Bus or subway ticket cost	Parking fee			
Weights	0.118	0.124	0.119	0.095	0.068	0.107	0.113	0.133	0.124

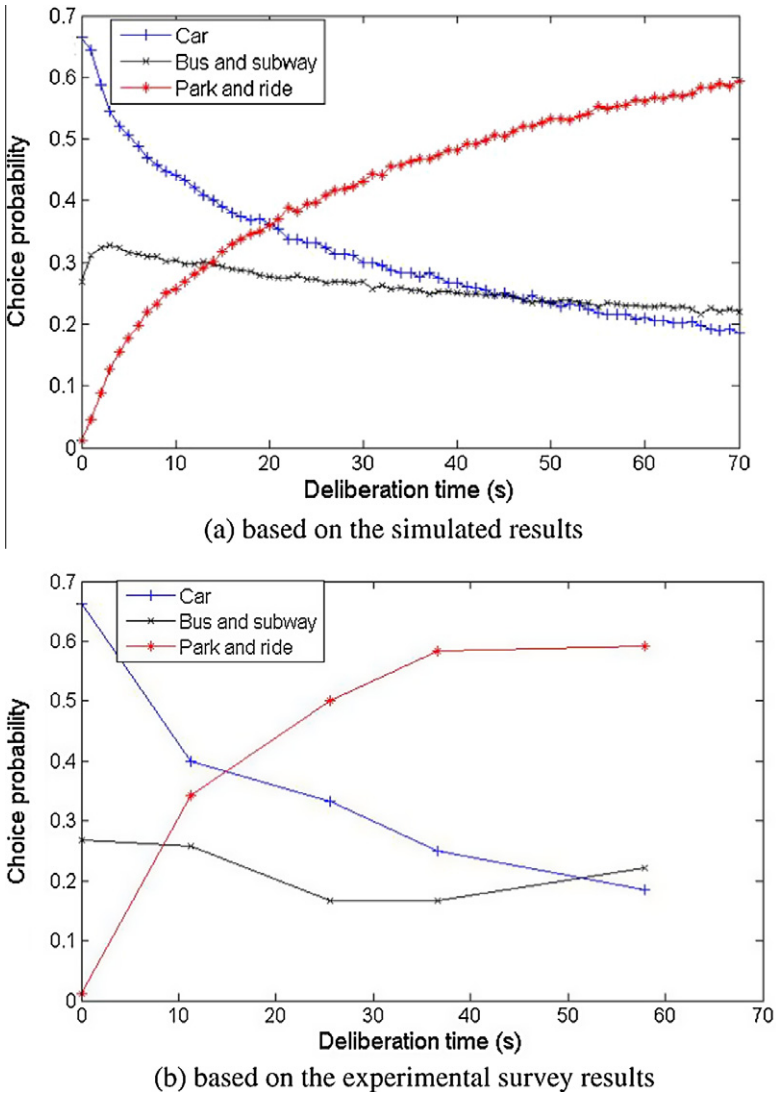


Fig. 3. The relation between deliberation time and mode choice probability by travel mode.

estimated. The proposed DFT-based model can be used to further analyze the dynamic deliberation process for the park-and-ride decision.

5. Analysis of *Park and Ride* decision behavior using the proposed model

In this section, the proposed DFT-based decision behavior model is used to analyze different types of decision making process and various variables are also examined. The following analyses are based on the simulated results of the proposed model.

5.1. Modeling decision process for individual traveler

The accumulation preference varies from person to person. Moreover, each individual traveler's momentary attention shifts stochastically from one factor (attribute) to another from time to time. The state of accumulation preference can reflect the dynamic deliberation process of travelers. The state of accumulation preference can reflect the dynamic deliberation process of travelers. For example, certain travelers may become hesitant when they have tradeoffs among multi-mode choices and need a long deliberation time to make a decision while others are more direct and may only need a short deliberation time to make a decision. In Section 4, 20,000 simulation runs of decision processes are executed. According to the observa-

tion and summary of all the simulation results, the decision processes of travelers are generally classified into three categories in this study: (1) simple decision, (2) indecision, and (3) preference reversal.

The explanation for these categories are explained in Sections 5.1.1–5.1.3 and examples of the traveler's decision processes are illustrated in Figs. 4–6. The horizontal axis represents deliberation time, and the vertical axis indicates the state

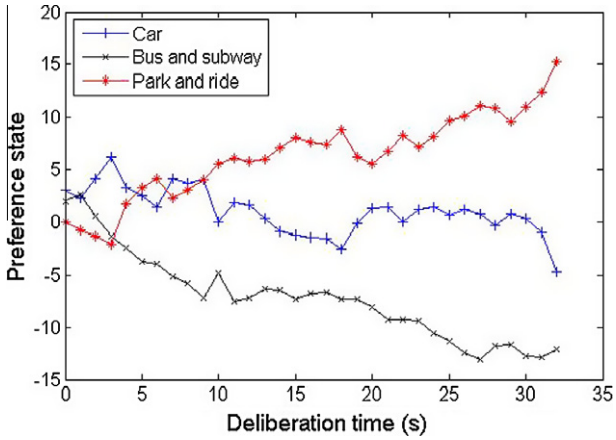


Fig. 4. Simple decision process for a mode choice.

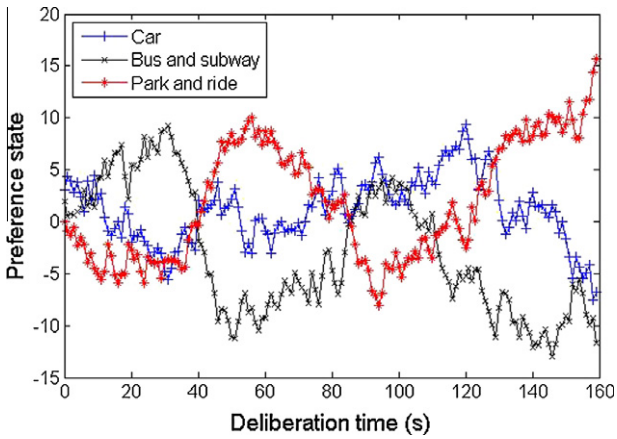


Fig. 5. Example of indecisive decision process.

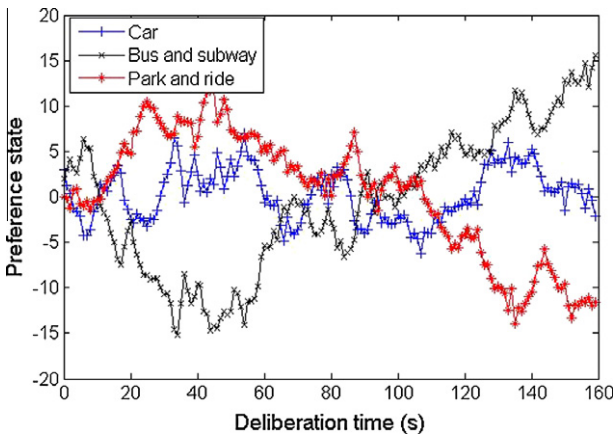


Fig. 6. Example of preference reversal for a mode choice.

of preference for each travel mode. Each trajectory in each figure represents the accumulation preference for each travel mode in a simulation run. No deliberation time is predefined so the deliberation process continues until one of three preference states exceeds the decision threshold. The decision threshold value for each mode choice is assumed to be 15. Once the accumulation preference state reaches 15, the choice for a mode will be made.

5.1.1. Simple decision

In the situation of a "simple decision", the traveler can make a direct decision without much hesitating. Fig. 4 shows one example of a "simple decision" process. The accumulation preference of each mode choice is gradually increasing or decreasing over time without significant fluctuation. The traveler with such a decision process usually considers fewer factors and requires a shorter deliberation time. This also shows that the cognitive capability of such a traveler is limited in the decision process.

5.1.2. Indecision

Fig. 5 shows that the accumulation preference states fluctuate over time in the dynamic decision process of an indecisive traveler. Fig. 5 shows that the preference state for each mode dominates a traveler's decision interchangeably as the deliberation time increases. The decision maker chooses a different travel mode depending on the deliberation time. The "tradeoff process" of multimode choice shows the hesitance of a traveler during an indecisive decision making process. This decision process usually needs a longer deliberation time. As shown in Fig. 5, the decision for this specific traveler will not be made until 160 s.

5.1.3. Preference reversal

Fig. 6 shows an example of the decision process with preference reversal. The mode with the highest preference state only dominates for a period of time and another travel mode replaces it if the decision threshold is not reached. In other words, the traveler might have made a different choice if the deliberation time is shorter or the decision threshold is lower. Fig. 6 shows that *Park and Ride* dominates for a period of time and then the dominance shifts to *Bus and Subway*. This example indicates that the traveler gives more preference for one travel mode for a period of deliberation time and will shift to choose another travel mode as more factors are considered due to a longer deliberation time. Generally, the deliberation time for the "preference reversal" case is relatively longer than the "simple decision" case. Different from the indecisive case, the fluctuation of the "preference reversal" is less frequent but has larger amplitude.

5.2. The effect of deliberation state threshold

The deliberation state threshold value has an important effect on the decision behavior. If the deliberation state threshold was set to a low value, a choice would quickly be made based on a weak preference and lead to an undesirable result. If the deliberation state threshold was set to a fairly high value, a choice would be made based on a strong preference and more likely to result in a positive outcome. Therefore, a high deliberation state threshold is likely to increase the deliberation time, giving the traveler more time to conduct a more thoughtful evaluation. In other words, analyzing a careless and impatient person's decision process requires a lower threshold. On the other hand, analyzing a thoughtful and patient person requires a higher threshold (see Fig. 7).

To test the effect of the deliberation state threshold, the threshold range of 0–25 is used in this simulation analysis. 20,000 simulation runs were conducted for each threshold value. Fig. 7 shows the final results. The choice probability for *Car* gradually decreases and that for *Park and Ride* increases as the deliberation threshold value increases. Compared with *Car*, the choice probability for *Bus and Subway* decreases more slowly as the deliberation threshold value increases.

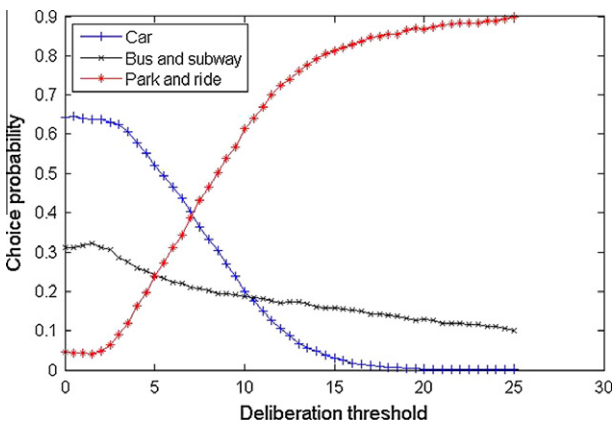


Fig. 7. The relation between deliberation threshold and mode choice.

According to the results, the impatient traveler is likely to choose *Car*, while a more thoughtful and patient traveler may tend to choose *Park and Ride*. It is also found in our experiment that the higher the deliberation state threshold value, the longer the required deliberation time is for a traveler to make a final choice.

5.3. Effect of initial preference

To examine the effects of initial preferences on the decision process, the ratio of the initial preference values for *Car* to the deliberation threshold changes from zero to one in this simulation analysis. 20,000 simulation runs were conducted for each initial preference and the results are summarized in Fig. 8. This figure shows that the choice probability for *Park and Ride* gradually decreases as the value of initial preference for *Car* increases. Once the initial preference ratio for *Car* passes 0.625, the choice probability for *Car* starts to exceed those of *Park and Ride* and *Bus and Subway*.

It is found in our experiment that the deliberation time decreases as the value of initial preference ratio for *Car* increases as shown in Fig. 9. This fact shows that the higher the value of the initial preference for *Car*, the more quickly the traveler would make a choice. Based on this analysis, it is suggested that one should reduce travelers' dependence on *Cars* during a decision process to increase the relative choice probability of *Park and Ride*. For example, providing free transit transfer tickets would be an incentive to reduce the traveler's dependence on *Cars* (Eriksson, Garvill, & Nordlund, 2008; Fujii & Kitamura, 2003; Verplankena, Walkera, Davisb, & Jurasek, 2008).

5.4. Effect of comfort level and parking fee

The influencing factors introduced in Section 3.2 are critical to a traveler's decision process. In this paper, the comfort level of public transportation and parking fees at the park-and-ride facilities are chosen as two critical factors to discuss because these two are critical factors based on the survey results in this study.

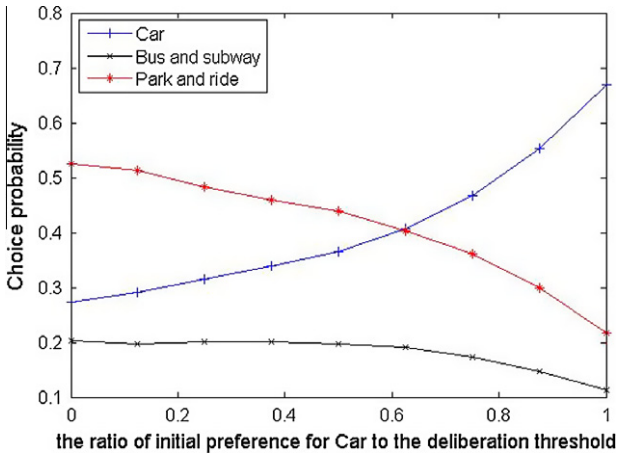


Fig. 8. The relation between the initial preference and mode choice.

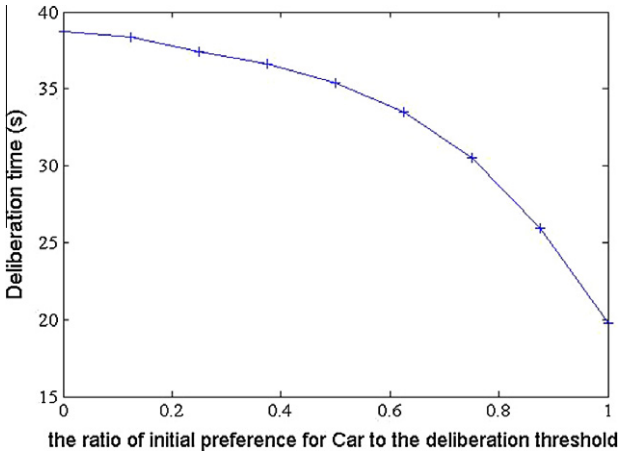
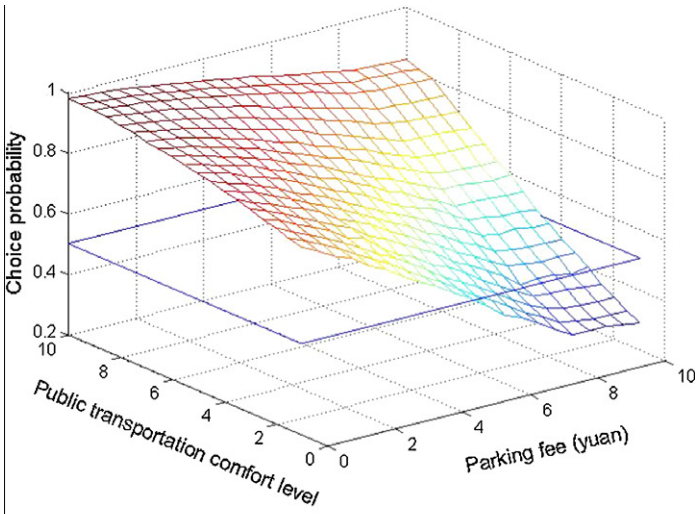
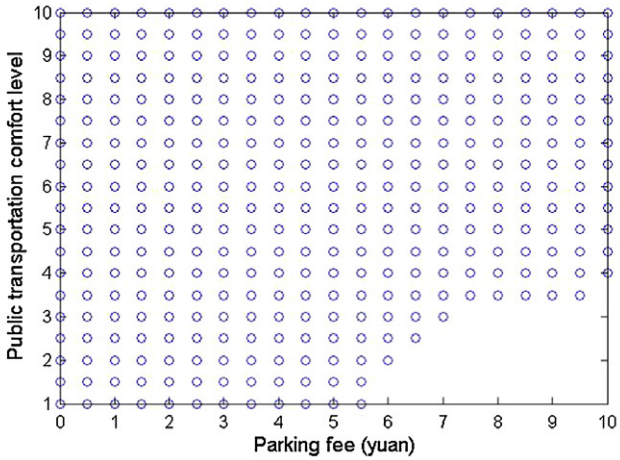


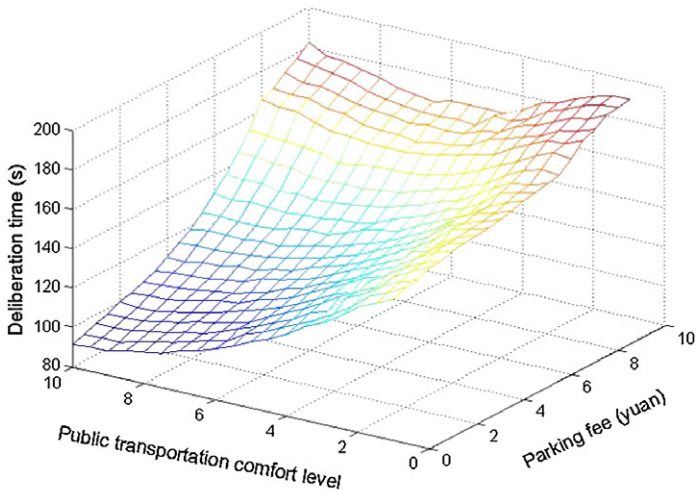
Fig. 9. The relation between initial preference and deliberation time.



(a) Choice probability for *Park and Ride*



(b) The hollow circle points distribution for *Park and Ride*



(c) Deliberation time by comfort level and by parking fee

Fig. 10. The decision behavior for *Park and Ride* by comfort level and parking fee.

Fig. 10a illustrates the three dimensional plot for the choice probabilities of *Park and Ride* under different public transportation comfort levels and parking fees. Fig. 10a is intercepted by a 2-D space when the probability for *Park and Ride* is highest. The intercepted area is illustrated in Fig. 10b. This is an example showing the traveler's decisions under different situations. Each circle point indicates a pair of influencing factors that produce the choice of *Park and Ride*. The choice probability of *Park and Ride* increases with increasing comfort levels and decreasing parking fees. In this example, when the parking fee at the park-and-ride facility is higher than six yuan and the comfort level for public transportation is less than 3, the travelers will not choose *Park and Ride*. Fig. 10c shows the distribution of deliberation time under different comfort levels and parking rates. The deliberation time is longer when the parking fee is higher and *Bus and Subway* is not comfortable. This fact indicates that it takes a long deliberation time for travelers to consider the tradeoffs among multi-mode choices based on the multiple attributes. When the comfort level of public transportation increases and parking fee for the park-and-ride facility decreases, travelers will be more likely to quickly choose *Park and Ride*.

6. Conclusions

Park and Ride is a kind of traffic demand management solution to mitigate traffic congestion in urban cities. Previous research mainly used static random utility theories to analyze the park-and-ride decision behavior rather than focusing on the dynamic deliberation process of travelers. This paper discusses the decision making behavior of choosing *Park and Ride* from a psychological point of view. A decision process experiment is designed by the process tracing technology and conducted in Beijing. Based on the experimental survey data, the model parameters are estimated and the decision behavior model of *Park and Ride* is established by Decision Field Theory. The errors between the simulated results generated by the proposed model and the real-life experimental data proved that the decision behavior model of *Park and Ride* is reliable.

Based on the analysis results, three decision processes—simple decision, indecision, and preference reversal—are successfully simulated using the proposed model. It is found that the traffic intervention measures such as providing the additional park-and-ride information regarding facility locations, parking fee, available parking spots might be able to improve the carefully deliberative process in the decision process and then increase the utility of park-and-ride facilities. It is also suggested that one should reduce travelers' dependence on *Cars* during a decision process to increase the relative choice probability of *Park and Ride*. For example, providing free transit transfer tickets would be an incentive to reduce the traveler's dependence on *Cars*. Furthermore, increasing the comfort level of public transportation and providing free parking for the park-and-ride facility would push travelers to choose *Park and Ride*. Moreover, it is also found that these simulated results are helpful for analyzing travelers' decision processes. Effects of all the model parameters are tested to provide a better understanding of the decision making processes of the travelers. Therefore, the proposed model demonstrates its capability of analyzing park-and-ride decision behavior and providing policy makers with useful information for future promotion or planning for park-and-ride facilities.

Further research could further investigate the difference between DFT-based model for *Park and Ride* and the park-and-ride behavior model based on the static random utility theory. Moreover, DFT-based model could be further developed to investigate the development of the habitual park-and-ride behaviors. The findings would be helpful for researchers to understand the sophisticated decision process of long-term park-and-ride behaviors.

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References

Arne, R. H. (2004). Forecasting the demand for an employee Park and Ride service using commuters' stated choices. *Transport Policy, 11*, 355–362.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision Field Theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review, 100*(3), 432–459.

Busemeyer, J. R., & Diederich, A. (2002). Survey of decision field theory. *Mathematical Social Sciences, 43*, 345–370.

Busemeyer, J. R., & Townsend, J. T. (1992). Fundamental derivations from decision field theory. *Mathematical Social Sciences, 23*, 255–282.

Busemeyer, J. R., & Johnson, J. G. (2004). Computational models of decision making. In D. Koehler & N. Harvey (Eds.), *Handbook of judgment and decision making*. Blackwell Publishing Co..

Busemeyer, J. R., Johnson, J. G., & Jessup, R. K. (2006). Preferences constructed from dynamic microprocessing mechanisms. In S. Lichtenstein & P. Slovic (Eds.), *The construction of preference*. Cambridge: Cambridge University Press.

Busemeyer, J. R., & Johnson, J. G. (2008). Micro-process models of decision making. In R. Sun (Ed.), *Cambridge handbook of computational cognitive modeling*. Cambridge: Cambridge University Press.

Duan, K., & Li, J. Y. (2010). The application of Decision Field Theory in clothing style evaluation. *Journal of Donghua University (Natural Science), 36*(2), 175–178.

Diederich, A., & Busemeyer, J. R. (2003). Simple matrix methods for analyzing diffusion models of choice probability, choice response time, and simple response time. *Journal of Mathematical Psychology, 47*, 304–322.

Diederich, A. (2003). MDFT account of decision making under time pressure. *Psychonomic Bulletin and Review, 10*(1), 157–166.

Eriksson, L., Garvill, J., & Nordlund, A. M. (2008). Interrupting habitual car use: The importance of car habit strength and moral motivation for personal car use reduction. *Transportation Research Part F, 11*, 10–23.

Fujii, S., & Kitamura, R. (2003). What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change. *Transportation, 30*, 81–95.

Gao, F., & Wang, M. Z. (2010). Route choice behavior model with guidance information. *Journal of Transportation Systems Engineering and Information Technology, 10*(6), 64–69.

Gao, F., & Wang, M. Z. (2009). Process-oriented dynamic route choice model. *Journal of Transportation Systems Engineering and Information Technology, 9*(5), 96–102.

Glimcher, P. W. (2001). Making choices: The neurophysiology of visual-saccadic decision making. *Trends in Neurosciences, 24*(11), 654–659.

He, B. H., Wang, W., & Chen, J. (2009). A choicemodel of traveler preference for P&R facilities. *Journal of Harbin Institute of Technology, 41*(4), 243–246.

Huang, M., & Zhou, T. (2007). Probit-based stochastic equilibrium used in the demand forecasting of P&R planning. *Communications Standardization, 12*, 183–185.

Johnson, J. G., & Busemeyer, J. R. (2010). Decision making under risk and uncertainty. *Advanced Review, 1*, 736–749.

Johnson, J. G., & Busemeyer, J. R. (2005a). A dynamic, stochastic, computational model of preference reversal phenomena. *Psychological Review, 112*(4), 841–861.

Johnson, J. G., & Busemeyer, J. R. (2005b). Rule-based decision field theory: A dynamic computational model of transitions among decision-making strategies. In T. Betsch & S. Haberstroh (Eds.), *The routines of decision making*. Mahwah, NJ: Lawrence Erlbaum Associates.

Jacoby, J., Jaccard, J., Kuss, A., Troutman, T., & Mazursky, D. (1987). New directions in behavioral process research: Implications for social psychology. *Journal of Experimental Social Psychology, 23*, 146–175.

Li, Y. L. (2011). *Research and implementation on fashion style decision making model*. Dissertation, Donghua University, Shanghai.

Molin, E., & Bos, I. (2009). *Exploring heterogeneity in park and ride preferences: A latent class mode*. TRB Annual Meeting CD-ROM.

McFadden, D. (1986). The choice theory approach to market research. *Marketing Science, 5*, 275–279.

Payne, J. W. (1976). Task complexity and contingent processing in decision-making: An information search and protocol analysis. *Organizational Behavior and Human Performance, 16*, 366–387.

Qin, H. M., Guan, H. Z., Ao, X. L., & Liu, Y. (2012). Park and ride survey analysis. *Urban Transport of China, 10*(1), 80–83.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative Decision Field Theory: A dynamic connectionist model of decision making. *Psychological Review, 108*(2), 370–392.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*, 59–108.

Rayner, K. (1978). Eye movements in reading and information processing. *Psychological Bulletin, 85*, 618–660.

Stern, E. (1999). Reactions to congestion under time pressure. *Transportation Research Part C, 7*, 75–90.

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011). *A handbook of process tracing methods for decision research: A critical review and user's guide*. New York: Psychology Press.

Townsend, J. T., & Busemeyer, J. R. (1989). Approach–avoidance: Return to dynamic decision behavior. In C. Izawa (Ed.), *Current issues in cognitive processes: The Tulane Flowerree symposium on cognition* (pp. 107–133). Hillsdale, NJ: Erlbaum.

Verplankena, B., Walkera, I., Davisb, A., & Jurasek, M. (2008). Context change and travel mode choice: Combining the habit discontinuity and self-activation hypotheses. *Journal of Environmental Psychology, 28*, 121–127.

Xiong, P., & Yang, D. Y. (2008). Application of disaggregated model in park and ride choice behavior. *Journal of Shenzhen University Science and Engineering, 25*(2), 206–210.