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Influence of parking on train station choice under uncertainty for park-and-ride users

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Abstract

This paper presents a station choice model for park and ride (PnR) users based on uncertain parking attributes, such as parking search time (PST). In order to take into account uncertainty in PnR users' choice process, a mixed logit model was developed within the framework of the discrete choice theory, the utility function in the model was established using a mean-variance approach under the cumulative prospect theory framework proposed Tversky and Kahneman [1]. A stated preference survey was designed for studying PnR users' preference of stations, which was influenced by parking conditions at a train station. The experimental design was optimized using the D-optimality criterion. Our results show that the number that parking bays left in PnR facilities at given access time, parking cost including parking fees and fines and the variation of PST are important factors affecting PnR users' station choice. PnR users were risk averse toward the variation of PST, which means that a PnR user is willing to choose a station with less uncertain or variation of PST.

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Keywords: station choice; risk averse; variation of parking search time; mixed logit; cumulative prospect theory.

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1. Introduction

The current capacity of 15,000 park-and-ride (PnR) car bays in Perth, Western Australia is far below the levels required to cater for the demand of PnR users [2]. This not only increased parking search time (PST), but also impacted PnR users' decision on choosing departure train station, as evidenced by a survey conducted by University of Western Australia and Curtin University in July 2012, covering a subset of Perth's train stations. Parking capacity, parking availability, parking cost and the variation of PST are vital for understanding PnR users' parking search strategies and station choice under PST uncertainty.

This paper aims to estimate train station choice under PST uncertainty for PnR users using a mixed logit model under the cumulative prospect theory framework proposed by Tversky and Kahneman [1]. Except variation of PST, we also investigated relationships between access time, parking availability, parking capacity, usual PST, the worst PST, parking fees, fines and violation control frequency and station choice. PnR users' risk attitude toward variation of PST was measured to understand its influence on preference of a station. The choice experiments were designed and optimized using the D-optimality criterion that is minimizing the determinant of the asymptotic variance-covariance (AVC) matrix.

The paper is structured as follows: The next section of the paper briefly reviews the previous studies of station choice, especially choice influenced by parking attributes. The third section describes the data collection methods and models for station choice under PST uncertainty. Results are presented in the section four. The paper concludes with a discussion of key findings and implications of our observations on station choice under PST uncertainty.

2. Related work

One of earliest studies of station choice, conducted by Kastrenakes [3], found location of station, access time, frequency of service and generalized cost were the most important factors influencing railway station choice, and a logit model of railway station choice was developed based on these factors for forecasting rail ridership in New Jersey area. Later, access mode, distance (between the origin and the chosen station) and additional facilities available at the stations were also shown to be very important factors affecting the choice of departure station[4-6]. To understand the trade-off between station and access mode choice, nested logit model and cross nested logit model were proposed byDebrezion, et al. [7]. This model holds advantages over previous studies by integrating all kinds of train station service quality and facility attributes, such as parking capacity parking availability, train schedule reliability.

Current studies examining the choice of train stations moved away from the simple multinomial logit (MNL) specification to more complicated models, considering more relevant variables, and accounting for preference heterogeneity. Even with these efforts, the prediction accuracy of station choice models hasn't been improved significantly. This could be due to lack of knowledge of how PnR users choose their station, especially in situations with uncertainty, such as parking availability and variability of PST. Whether these uncertain circumstances will change behaviors, such as switching travel modes or stations, or to what extent, is under research. In addition, traditional models haven't considered PnR users' risk attitude towards these uncertain circumstances or variables.

Uncertainty affecting the decision process for modal choice comes from two resources, one is the combination of day-to-day variability in the transport network and commuters 'unpredictable network conditions', such as travel time delay due to a unexpected festival event [8], and another one is the degree confidence in their assessment of the network conditions. Some of the uncertain factors have been studied in other choice situations. One of earliest studies conducted by Gaver [9] found that individuals usually adjust their departure time to compensate for uncertainty about the time needed to complete a trip. Later, Menaske and Guttman [10] modelled the effect of travel time uncertainty on access mode and route choice by integrating the traveler's attitude to risk. That is, they believed travelers, who were averse to risk, would choose the more certain modes and routes, and vice versa, risk takers would choose quickest modes and routes, even if the expected traffic conditions are worse. Hunt and S. Teply [11] found that parking search time is also a uncertain factor affecting parking location choice, and developed a nested logit model of parking location choice which includes parking search time. The degree of overcrowding on trains has also been found significant mode choice determinant by Whelan and Johnson [12]. They developed the PRAISE

(Privatisation of Rail Services rail) operations model based upon journey purpose, journey time and degree of overcrowding on trains.

In summary, many uncertain attributes can affect the station choice for PnR commuters. In the paper, we only address on the effect of variation of parking search time and other parking attributes on station choice for PnR users.

3. Methodology

3.1. Data collection

A stated preference method was used to investigate the preference of PnR users' station choice. Train users were asked to select one of two stations in each of 4-6 combinations of attribute levels, given conditions of assuming they are reasonable. A station choice survey questionnaire was designed with two choice sets and nine attributes. We summarised these attributes and their levels in Table1. Twelve scenarios were developed, using D-optimal designs. Surveys were conducted from November to December, 2014 at seven train stations in Perth, Western Australia. About 600 train users filled in the survey with 4-6 scenarios each. A total of 2,379 scenarios were collected.

Table 1. Attributes and attributes level in stated preference experiment

No.	Attributes	level	description
1	Access time	3	①7:00am ②7:30am ③8:00am
2	Capacity of a PnR parking facility	3	①100 ②500 ③1000
3	Usual parking search time	3	①1mins ②5mins ③10mins
4	The ratio of the worst parking search time from the usual parking search time	3	①1 ②4 ③8
5	The probability that the worst parking search time occurs in one month	2	①5% ②20%
6	Parking availability	3	①0 ②10% ③20%
7	Parking fee in PnR parking facilities	3	①$2/day ②$4/day ③$6/day
8	Parking fine due to illegal parking	3	①$40 ②$60 ③$80
9	Control frequency for illegal parking	3	①once a month ②once a week ③once a day

3.2. Station choice models

The choice model in the paper was developed based on the discrete choice theory. Mixed logit models were applied for modelling station preference behavior because the station choice probability can be a mixture of logits with the mixing distribution and mixed logit models can approximate any choice models [13]. Its general specification is expressed as equation (1).

$$p_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \quad (1)$$

Where:

$$L_{ni}(\beta) = \frac{e^{\beta' x_{ni}}}{\sum_{j=1}^{J} e^{\beta' x_{nj}}} \quad (2)$$

p_{ni} is the probability that the respondent n chooses the i^{th} alternative station; $L_{ni}(\beta)$ is the logit probability evaluated at parameters β ; and $f(\beta)$ is a density function .

The utility functions depend of whether parking is available or not in PnR facilities. Parking availability is set as a constraint in the choice model. When available, the number of parking bays left in PnR facilities at a given time and the parking fees represent the main source of utility; when unavailable, the usual PST and its variation, the parking fines for illegal parking and the parking violation control frequency are determinants of utility considered in the logit model. Therefore, the observed part of utility function in mixed logit model is a two-part function. Its specification is shown as:

$$V_i = \begin{cases} \beta_1 \times f(N_i^{pbay}) + \beta_2 \times fee_i^p & pa > 0 \\ \beta_3 \times V(VPST_i) + \beta_4 \times fine_i^p \times fre_i^{con} & pa = 0 \end{cases} \quad (3)$$

Where fee_i^p is the parking fee at the station i ; $fine_i^p$ is the fine for illegal parking around the station i ; fre_i^{con} is control frequency for illegal parking around station ; N_i^{bay} is remaining parking number, that respondents think ,at given arrival time to station i . It depends on the parking capacity (pc), parking availability (pa) and the arrival time to the chosen station. However, the demand for parking bays increases in the morning with car parks being fully occupied during peak hours. In other words, the later the time of arrival at the train station, the higher the competition between PnR users for securing a parking bay. Here, we took 7:00am as reference point and assumed the relationship among them can be written as $N_i^{pbay} = pa \times pc$. In order to accurately identify the effect of remaining parking number on station choice, we tested three forms, namely, linear, power, exponential function and the linear form is recommended according to the performance of the model (see Table 2). The formula is shown as:

$$V_i = \beta_1 N_i^{pbay} + \beta_2 fee_i^p \quad (4)$$

Table 2. Statistical results for three specification forms

	Linear	Power	Exponential
	$\beta_1 N_i^{pbay} + \beta_2 fee_i^p$	$\beta_1 \left(N_i^{pbay}\right)^{\alpha_3} + \beta_2 fee_i^p$	$\beta_1 e^{N_i^{pbay}} + \beta_2 fee_i^p$
Log likelihood	-817.89	-822	-885.76
Inf.Cr.AIc	1645.8	1656	1781.5

$VPST_i$ in equation (3) is the variation of parking search time at station i , and is equal to the longest parking search time minus usual parking search time, namely, $VPST_i = wpst_i - upst_i$; $V\left(VPST_i\right)$ is a utility function of the variation of PST, developed under cumulative prospect theory (CPT). The general function form of utility within CPT includes the value function $v\left(\Delta x_i\right)$ and the weighting function $\pi\left(p_i\right)$ as follows:

$$V\left(x_i, p_i\right) = \sum_{i=1}^{n} \pi\left(p_i\right) v\left(\Delta x_i\right) \quad (5)$$

The value function in CPT is defined over gains and losses separately. Here, Δx is used to indicate the difference between the real value and a reference point, when Δx is greater or equals to zero is gains, otherwise is losses; p_i is probability that the i^{th} outcome occurs; $\pi\left(p_i\right)$ is the subjective weighting function derived from the outcome cumulative probability; and $v\left(\Delta x_i\right)$ is a value depending on gains or losses. These specifications are shown in (6) and (7).

$$v(\Delta x_i) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases} \quad (6)$$

$$\begin{aligned}\pi^{+}\left(p_i\right) &= w^{+}\left(p_i+\cdots+p_n\right)-w^{+}\left(p_{i+1}\cdots+p_n\right) \qquad 0\le i\le n \\ \pi^{-}\left(p_j\right) &= w^{-}\left(p_{-m}+\cdots+p_{-j}\right)-w^{-}\left(p_m+\cdots+p_{j-1}\right) \quad m\le -j<0\end{aligned} \tag{7}$$

Usual PST is taken as the reference point in the paper, so the gains represent the difference between the best PST (or the shortest PST) and usual PST and the losses is the difference between the worst PST (longest) and usual PST. Because data from the pilot and main survey indicated very low gains, they are ignored in this paper. Moreover, only the power and Tversky-Kahneman forms were chosen for the value function and the weighting function, because these forms have been successfully used by previous studies to explore route choice [14]. Therefore, the value function and weighting function for the variance of PST can be written as:

$$v\left(\Delta x_i\right)=\lambda\left(-\Delta x_i\right)^{\beta}=\lambda\left(wpst_i-upst_i\right)^{\beta} \tag{8}$$

$$w^{-}\left(p_i\right)=p_i^{\delta}\Big/\left[p_i^{\delta}+\left(1-p_i\right)^{\delta}\right]^{\frac{1}{\delta}} \tag{9}$$

Where *wpst* is the worst parking search time; *upst* is the usual parking search time; λ,β is an estimated parameters and β can indicate commuters' risk attitude; and p_i is the frequency that the longest PST occurs in one month at station i . Substituting equations (8) and (9) in (5), the utility function for the variability of PST is shown as:

$$V\left(VPST\right)=\pi\left(p_i\right)v\left(\Delta x_i\right)=\lambda\left(wpst_i-upst_i\right)^{\beta}\times p_i^{\delta}\Big/\left[p_i^{\delta}+\left(1-p_i\right)^{\delta}\right]^{\frac{1}{\delta}} \tag{10}$$

Replacing equation (4) and (10) in (3), the observed part of utility function of parking attributes for station choice can be written as:

$$V_i=\begin{cases}\beta_1\times N_i^{pbay}+\beta_2\times fee_i^{p} & pa>0\\ \beta_3\times\left(wpst_i-upst_i\right)^{\beta}\times p_i^{\delta}\Big/\left[p_i^{\delta}+\left(1-p_i\right)^{\delta}\right]^{\frac{1}{\delta}}+\beta_4\times\left(fine_i^{p}\times fre_i^{p}\right) & pa=0\end{cases} \tag{11}$$

Assuming respondents must park their cars in PnR area when there are parking bays in PnR area, the overall utility function can be written as equation (12):

$$\begin{aligned}U_i &= V_{pai}+V_{npai}+\varepsilon_i=\beta_1\times N_i^{pbay}+\beta_2\times fee_i^{p}+\\ &\beta_3\times\left(wpst_i-upst_i\right)^{\beta}\times p_i^{\delta}\Big/\left[p_i^{\delta}+\left(1-p_i\right)^{\delta}\right]^{\frac{1}{\delta}}+\beta_4\times\left(fine_i^{p}\times fre_i^{p}\right)+\varepsilon_i\end{aligned} \tag{12}$$

Where V_{pai} is the observed utility at the station i when pa_i is greater than zero; V_{npai} is the observed utility when pa_i equals to zero; and ε_i is the error item for the station i^{th} .

4. Results

4.1. Estimation of parameters

The parameters of the station choice model were estimated using multinomial logit and mixed logit models with the Nlogit software [15]. In mixed logit model, parameters β_1,β_3 are assumed random and to follow the triangular or normal distributions. The results are summarized in Tables 3 to 5.

Table 3. Multinomial logit model with linear utility function

Choice	Coefficient	Standard error	z	Prob. $z > \lvert Z \rvert$	95% Confidence Interval	
β_1	1486***	0.00534	********	0.0000	1486.85	1486.87
β_2	-1.04886***	0.05379	-19.50	0.0000	-1.15429	-0.94342
β_3	-0.020488***	0.00548	-3.74	0.0002	-0.03123	-0.00974
β_4	-0.00279	0.00548	-1.05	0.2927	-0.008	0.00241
C[#]	-0.16444**	0.07789	-2.11	0.0348	-0.3170	-0.01177
Number of obs =1358						
Inf.Cr.AIC =1873.6						
Log likelihood = -931.79661						

Note: ***, **, * = Significance at 1%, 5%, 10% level.

Table 3 shows a significant effect of the number of parking bays remaining in the PnR facilities, the parking fee and variation of PST on the station choice for PnR users. High availability of parking bays, low parking fee and less variation of PST are increasing the probability that the station is chosen.

Table 4 Mixed logit model with random parameters following normal distribution

Choice	Coefficient	Standard error	z	Prob. $z > \lvert Z \rvert$	95% Confidence Interval	
	Random parameters in utility functions					
β_1	46.2948	0.4570D+10[*]	0.00	1.000	**********	**********
β_3	-0.00071	0.00400	-0.18	0.8588	-0.00856	0.00713
	Non-random parameters in utility functions					
β_2	-0.1579***	0.05387	-2.96	0.0031	-0.26508	-0.0539
β_4	-0.00566	0.00468	-1.21	0.2262	-0.01482	0.00351
β	5.047272**	2.27829	2.22	0.0267	0.51890	9.51264
δ	0.29428***	0.03079	9.56	0.000	0.23394	0.35642
	Distns. ofRPs. Std. Devs or limits of triangular					
$Ns\beta_1$	0.03517	0.3788D+11	0	1.00	**********	***********
$Ns\beta_3$	0.00194	0.01016	0.19	0.8485	-0.1797	0.02185
Number of obs.=1358						
Inf.Cr.AIC=1644.3						
Log likelihood=-814.17						

Note: ***, **, * = Significance at 1%, 5%, 10% level.

The parameters in Table 4 were estimated for a mixed logit model with β_1, β_3 following normal distributions. Even though the values of the parameters are different from ones in Table 3, their sign remains the same. The model has better goodness-of-fit results, but suggests that the parameters may not be random. Similar results were obtained with a triangular random distribution of the parameters (see Table 5). However, the model with random parameters following normal distribution has better goodness-of-fit than the one with random parameters following triangular distribution based on the statistical indexes. Therefore, the model with parameters following normal distribution is recommended to capture PnR users' choice for departure train station under parking uncertainty.

[#] C is station 1-specific constant.
[*] The value indicates the parameter cannot be random;

Table 5. Mixed logit model with random parameters following triangular distribution

Choice	Coefficient	Standard error	z	Prob. $z > \lvert Z \rvert$	95% Confidence Interval	
	Random parameters in utility functions					
β_1	91.0325	691.5102	0.13	0.8953[†]	-1264.3027	1446.3676
β_3	-0.1165D-04	0.00091	-0.01	0.9898[‡]	-0.17989D-02	0.17756D-02
	Non-random parameters in utility functions					
β_2	-0.15764***	0.05926	-2.66	0.0078	-0.27380	-0.04148
β_4	-0.00503	0.00371	-1.35	0.1757	-0.0123	0.00225
β	6.51412	6.33082	1.03	0.3035	-5.98406	18.92229
δ	0.30832	2.35560	0.13	0.8959	-4.30858	4.92521
	Distns. of RPs. Std. Devs or limits of triangular					
$Ts\beta_1$	10.2233	769.2380	0.01	0.9894	-1497.4554	1517.9020
$Ts\beta_3$	0.56768D-04	0.00444	0.01	0.9898	-0.86746D-02	0.87611D-02
			Number of obs.=1358			
			Inf.Cr.AIC=1644.4			
			Log likelihood=-814.4886			

Note: ***, **, * = Significance at 1%, 5%, 10% level.

4.2. Risk attitude

According to cumulative prospect theory, the parameter over the gains or losses can indicate respondents' risk attitude for gains or losses. In the recommended model, parameter β can show the respondents' risk attitude for larger variation of PST. In the model, the estimate of β is 5.05. It is statistically significant and has an effect on the shape of value function (see Figure 1-(a)), in which zero is taken as reference point, and the losses are calculated as differences between the longest PST and usual PST. The shape of value function is concave for losses, but the figure can still show that: 1) the higher the loss, the lower the value function becomes; and 2) the value from risk neutral ($\beta = 1$) is greater than the value from this model at the same losses. Therefore, the respondents are risk averse based on the data used in the paper.

Furthermore, the estimate of δ is 0.29428. Similar to β , it is also statistically significant and it does have an impact on the shape of the risk weighting function (see Figure 1-(b)). The results may suggest that the outcomes with low probabilities tend to be largely overweighted and the outcomes with high probabilities tend to be underweighted by respondents.

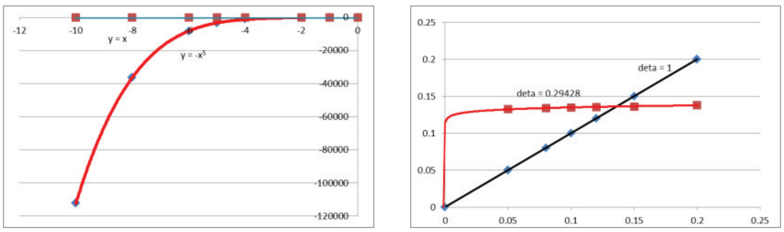

Figure.1. (a) Non-linear value function; (b) Non-linear risk weighting

[†] P value shows the random parameter 'distribution cannot be suitable.

Furthermore, the estimate of δ is 0.29428. Similar to β, it is also statistically significant and it does have an impact on the shape of the risk weighting function (see Figure 4). The results may suggest that the outcomes with low probabilities tend to be largely overweighted and the outcomes with high probabilities tend to be underweighted by respondents.

5. Conclusion

In this paper PnR users' station choice was analyzed using multinomial and mixed logit models. According to our knowledge, this is the first attempt to understand of PnR users' station choice under uncertain PST under combination of the cumulative prospect theory and the discrete choice theory.

A stated preference (SP) survey was conducted at seven train stations in Perth, Western Australia. The questionnaires used in the survey were designed based on D-efficiency approach. The SP data was modelled within discrete choice theory, and utility function is established separately for two situations (parking available or not in the PnR areas). When parking is available, an exponential function was used to capture the effect of the number of parking bays left in PnR facilities at given access time on station choice for PnR users. The mixed logit model with parameters of triangular distribution was found to be the best fit model, although the results suggest non-random parameters for parking availability and parking fee. When parking is unavailable in PnR facilities, variation of PST, parking fine and the frequency controlling illegal parking were considered in the model. In order to capture the effect of variation of PST, the part of utility function is developed within CPT and parameters were estimated. The results showed the effect of variation of PST is not significant, but respondents may display risk aversion for variation of PST and very weak non-linearity in risk weighting function. Larger variations of PST, higher parking fines and more frequent control for illegal parking, lead to lower utility functions and smaller probabilities that the station is chosen. The results of our study could provide useful insights for implementation of public transport policies (such as ticket price policy).

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