Modeling Heterogeneous Parking Choice Behavior in University Campuses

Fanyu Meng[a], Yuchuan Du[b,1], Yuen Chong Li[c], S.C. Wong[d]

a. Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong. TEL: +852 28592662. Email: 101366@tongji.edu.cn

b. School of Transportation Engineering, Tongji Univerisity, 4800 Cao'an Road, Shanghai, China. TEL: +86 21 69585712. Email: ycdu@tongji.edu.cn

c. Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong. TEL: +852 28592662. Email: joeyliyc@connect.hku.hk

d. Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong. TEL: +852 28591964. Email: hhecwsc@hku.hk

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1. Corresponding Author.

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Abstract

Studies of campus parking indicate more severe problems and a wider range of characteristics than commercial parking because of limited parking spots, special conditions, specific policies and enclosed space on university campuses. However, heterogeneous characteristics are usually ignored in analyses of campus parking behavior. In this paper, a mixed logit model is applied to analyze parking choice behavior on campus using data collected from a stated-preference survey on Siping Campus of Tongji University, Shanghai, China. The heterogeneity of individuals with various socio-demographic characteristics is evaluated by interaction terms and random parameters. Comparison between the proposed approach and the conditional logit model shows that the results of the mixed logit model are more interpretable because it is not limited by the independence from irrelevant alternatives assumption. Several key factors, such as gender and mid-term parking, that have considerable effects on campus parking choices are identified and analyzed. Important regularities are also concluded from elasticity analyses in every possible direction. Finally, the campus is divided into two areas according to the walking distance to a new parking lot currently under construction, and the modeling result shows that area-specific policies should be established because the two areas have quite distinct parking choice features.

Keywords: parking choice, university campus, heterogeneity, mixed logit model, stated preference, elasticity

1. Introduction

As the number of car owners grows ever larger, static traffic (parking and queueing at signalized intersection and toll station, etc.) and dynamic traffic (all the traffic running in the system with a certain speed) combine to form the basic structure of the urban traffic system. Because of the interference of static traffic on dynamic traffic, numerous research studies had been conducted to unify the major problems of parking management in an urban traffic system. For example, Matsoukis (1995) studied the major parking patterns, and then revealed the privatization of parking management in Greece. More quantitative analyses of parking systems and transit parking were considered toward the end of the twentieth century (Hwang and Lee, 1998, Merriman, 1998). Khattak and Polak (1993) have tested and modeled the effect of parking information service which provided real-time parking information of City Center parking facilities in Nottingham, England by measuring the travelers' responses, and the parking information delivery service was proved to be effective. Moreover, parking policy studies with economic concerns were also performed as one of the major research aspects in parking (Verhoef et al., 1995). Young and Taylor (1991) outlined the successful applications of microcomputer models to parking policy investigations. In recent years, parking studies have aimed to quantify the relationships between parking charges and other traffic or economic factors to set more acceptable and balanced transport policies. The influence of parking and road user charges on traffic and revenue was modeled and analyzed, with the results showing that a combined measure that partly converts parking charges to road user charges worked best as a balanced scheme (Bonsall and Young, 2010). Meanwhile, statistical analyses of combinations of static and dynamic traffic have been widely performed. For example, a model of curbside parking with stochastic vacancies was optimized by considering higher vacancy rates, which were found to be higher during busier times and at locations with heavier traffic (Arnott, 2014). Parking price theories have been applied to parking choice behavior, models that consider different parking price conditions and personal attributes. For example, cruising (searching for parking places) was studied as a choice model and conditions under which a driver would either pay for parking or continue to cruise were devised (Shoup, 2006).

As the diversity of parking research has increased, parking choice has drawn much attention from researchers. Arnott and Rowse (1999) used a probit model to investigate drivers' parking choices in a city, considering a linear combination of three major factors: driving distance, walking distance and parking fees. Moreover, various modeling methods have been tested and proven to be capable of depicting drivers' parking choice behavior in multiple situations (Bonsall and Palmer (2004). Among these modeling methods, discrete choice models have been widely applied in parking choice behavior studies with various influential factors considered in the models (Fukuda and Morichi, 2007, Mei et al., 2010, Nurul Habib et al., 2012). On the other hand, street and garage parking are the two most commonly considered alternatives when estimating the effect of prices together with other attributes (Kobus et al., 2013). Micro traffic simulation has also been incorporated into truck parking choice modeling to assess the potential effect of multiple parking policies (Nourinejad et al., 2014). Another recent study has modeled the relationship between parking facilities in one's home and mode choice behavior using a two-stage survey strategy and found that guaranteed parking at home heightened the possibility to drive to downtown areas (Weinberger, 2012).

The traffic system in a university campus with distinct parking patterns can be resembled with those of small cities which has various land uses (such as for education, residences and recreation) and multimodal nature of transportation on a campus (includes private cars, shuttle buses, cycling and walking) (Ison and Rye, 2008). In addition, the mini traffic system within a campus has more distinct and obvious peak hours and severe conflicts between demand and supply due to its limited area, especially for static traffic in an urban campus. Moreover, there is usually a dense residential area surrounding the university campus where students, staff and faculty reside, which interacts with the nearby traffic system and increases the probabilities of traffic congestion, accidents and parking demand (Daggett and Gutkowski, 2003). Hence, to deal with the traffic problems caused by university campus commuting, a systematic management scheme will be essential.

Transportation demand management (TDM) is playing an increasingly important role in releasing the traffic and environmental problems caused by university campus commuting, of which parking management is one of the most significant parts. Multiple studies have focused on introducing and optimizing modal split schemes on campuses to reduce vehicle demand and increase public transit services in a university campus, and it was found that TDM strategy is an essential factor (Balsas, 2003). Because the essence of transportation management in university campuses is more of a business than a municipal issue (Daggett and Gutkowski, 2003), the application of TDM to campuses emphasizes economic and sustainable management. Shoup (2005) proposed to manage campus parking at the University of California, Los Angeles by reforming the pricing of public transport and introducing parking fees. Rye and Ison (2005) analyzed the practicalities of charging employees parking fees by comparing 11 workplaces in the United Kingdom, five of which were university campuses. Comparison of these situations helped to identify the obstacles that hindered the pace of charging employees for parking. Focusing on policy-making in relation to parking management on campuses, Barata et al. (2011) surveyed parking supply and demand flows in the University of Coimbia campus and determined that the supply level was so low that lead to vehicle spillover. A logistic regression examined commuters' willingness to pay for parking on campus and the results were used to propose several policies. A similar study in Beijing analyzed traffic flow and driver behavior on a university campus (Shang et al., 2007). Riggs (2015) studied the effect of a survey in UC Berkeley regarding mode change and lessening parking demand, and concluded that 8% of the sample changed modes and adequacy, safety and convenience of the alternatives hindered mode selection.

The analysis of parking choice behavior on campuses is a popular topic for the application of TDM because understanding the nature of parking choices can help clarify the processes that cause congestion. Various researchers have studied parking choice behavior in the campus setting using multinomial logit (MNL) models with respect to the safety level, service level, convenience, for example. However, the heterogeneity of decision makers has never been considered in campus parking, though parking choices can vary among people with different demographic characteristics. As the independence of irrelevant alternatives (IIA) property of the traditional MNL model may not be useful in the campus setting, this paper proposes a discrete choice modeling method by comparing the conditional logit (CL) model and mixed logit (ML) model, both of which adopt interaction terms, and tests the heterogeneity of parking choice behavior on a university campus.

2. Data

2.1. Parking in Tongji University

There were 5,870 registered vehicles at Tongji University in 2013, of which nearly 40% were commuter vehicles in use on weekdays, and the rest were temporary vehicles from other communities, companies and organizations connected with the university. Both students and staff can register their vehicles to allow entry to the campus. This systematically burdens the parking supply and results in traffic disorder on campus. Therefore, proper parking management policies should be determined for Siping campus to balance parking demand and supply and enable the on-campus traffic system to run smoothly and organically.

In this study, the parking choice behavior in Siping campus of Tongji University was examined. The campus consists of two areas, Area A and B. Area A includes mainly working areas, classrooms and large recreational places, while Area B contains mainly residential halls and dormitories. There are 1,498 parking places on Siping campus, 309 of which are in four underground parking lots and 1,189 spaces in open-air areas (including both parking lots and curbside parking places). To enhance the parking facilities, a new large underground parking lot with 900 parking places will be provided in 2016. The parking spaces arrangement is illustrated in Figure 1. In addition to this, four major free parking spaces outside the campus (within 15-minute walking distance) were also considered in this study.

2.2. Stated Preference Survey

The stated preference (SP) survey is commonly applied to undertake econometric, road safety and choice behavior research because of its ability to present choice settings of individual (Ahmadi Azari et al., 2013). In this survey, four hypothetical scenarios were proposed to estimate the preferences of individuals. As reported previously (Zhang et al., 2006), the attributes that most influence the use of a parking lot include walking time, parking charges, degree of parking convenience, enforcement of laws and parking information. For the purpose of quantifying parking choice behavior and determining relative parking policies regarding parking fees, unquantifiable attributes were removed in this study.

The interviewees were given the choice of three alternatives in the hypothetical scenarios:

- Alternative 1: Open-air parking (OA), in which cars can park in open-air parking lots around the buildings with parking places restricted by lines (including curbside parking).
- Alternative 2: Underground parking (UG), in which cars can park in underground parking lots.
- Alternative 3: Off-campus parking (OC), in which cars can park in any parking lot, whether underground or open-air, outside Siping campus.

These three alternatives are characterized by three common attributes: parking charges, walking time and number of free hours (Table 1).

2.3. The Survey

The survey was conducted online on December 9 and 16, 2013, by inserting the questionnaire into the system for vehicle entrance license application. All teachers, staff and students have to update their license each year to be able to drive their cars onto the campus. The inclusion of the questionnaire was permitted by the Security Department of Tongji University, and anyone intending to obtain an entrance license through the application system was asked to fill out the questionnaire. The suggested time to complete the survey was 10-15 min as written in the questionnaire instructions to provide a better idea of the burden of this questionnaire.

Ultimately, 1,873 valid questionnaires were received, of which 998 were from Area A and 875 from Area B. According to the survey data, the explanatory variables were divided into two categories: parking lot attribute variables and individual characteristic variables (Table 2).

3. Methods

3.1. Conditional logit (CL) model

McFadden's CL model is considered to be a variant of the standard MNL model (O'Keefe, 2004), which is commonly adopted to evaluate the parking choice. The CL model theoretically ignores heterogeneity of individual and works as a contrast to the ML model because it is restricted to the IIA assumption.

The framework of CL model is based on random utility theory, which requires decision makers to choose the alternative with the largest utility. In this theory, the utility of the nth alternative for individual i is described as follows:

$$Z_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

where Z_{in} is the proposed utility, V_{in} is the non-stochastic term and ε_{in} is the random error term. In the CL approach, the term V_{in} is always described as a summation of two terms, and then the utility function becomes

$$Z_{in} = \sum_{r=1}^{R} \beta_{nr} X_{ir} + \sum_{s=1}^{S} \gamma_{is} W_{ns} + \varepsilon_{in} \tag{2}$$

where β_{nr} and γ_{ns} represent the coefficient vectors of alternative and individual characteristics, respectively, R is the number of choice specific variables and S equals the number of variables describing individual attributes.

According to the utility function and random utility theory, the probability of the mth parking choice being chosen by individual i is described as follows:

$$\Pr(Y_i = m) = \frac{\exp(Z_{im})}{\sum_{j=1}^{M} \exp(Z_{ij})} = \frac{\exp(\sum_{r=1}^{R} \beta_{mr} X_{ir} + \sum_{s=1}^{S} \gamma_{is} W_{ms})}{\sum_{j=1}^{M} \exp(\sum_{r=1}^{R} \beta_{jr} X_{ir} + \sum_{s=1}^{S} \gamma_{is} W_{js})} \tag{3}$$

where M is the number of available alternatives and m is the one to be chosen. The probability of individual i choosing all M alternatives should be 1.

3.2. Mixed logit (ML) model

The ML model is also based on random utility theory and the utility maximization assumption. ML probabilities can be regarded as an integral of standard logit probabilities over a density of parameters, which is a weighted average of the standard logit formula using different values of parameter β (Ye and Lord, 2014). The probability function of the ML model is

$$P_r(Y = m) = \int \frac{\exp[X_{im}\beta]}{\sum_{j=1}^{M} \exp[X_{ij}\beta]} f(\beta|\theta) d\beta \tag{4}$$

where θ is the density $f(\beta|\theta)$. Due to the random parameters in the ML model, the heterogeneity of individuals can be considered in the model.

Random parameters

The random parameters of the ML method are considered to be the key factors. In practice, it is always difficult to determine which variable has a random parameter and the distribution it follows (Kim et al., 2013). In this study, we tested all of the variables that were significant at the 0.1 level or above by assuming that they followed three widely used distributions: normal, lognormal and uniform. T-tests and goodness-of-fit approaches were used to determine the significant variables, optimal distributions of random parameters and the quality of the models. Parameters with statistically significant means and standard errors according to t-tests were regarded as random parameters (Milton et al., 2008).

In the ML model, the random parameter β^* can be formulated as the follows:

$$\beta^* = b_m + s_m \varepsilon_\beta \tag{5}$$

where b_m is the mean of β^* and s_m is the scale parameter for ε_β, and in this case, $\varepsilon_\beta \sim U(-1,1)$. b_m and s_m are estimated parameters that identify the random parameter β^*. The differences between the preferences of decision makers can also be examined using the random parameters by providing a mean and standard deviation in the ML interaction model (Ye and Lord, 2014). Therefore, the ML model is easier to interpret and more suitable for describing the parking choice process on campuses than the CL model.

3.3. Interaction model for heterogeneity

To test the specific influence of each variable on each alternative, we applied the interaction terms for each variable and each alternative. Therefore, the original explanatory variables were all replaced by interaction terms in the proposed parking choice models.

The interactions between different variables are also worth exploring in a logit model. To avoid negative influences resulting from too many dependent variables in the logit model, we set up another series of models using each modeling method, referred to as the interaction model, and applied the interaction terms and parking-lot dummy variables to test the heterogeneity of various variables. The interaction terms were thus formed by multiplying the individual factor variables by the parking-lot attribute variables to determine the relationships between them. The interaction models can provide useful information, e.g., the heterogeneity of parking choice taste within a group of individuals, which is helpful when determining parking policies for various groups of individuals.

4. Results and Discussion

In this study, the entire modeling process was conducted in SAS 9.3 by applying the multinomial discrete choice (MDC) procedure. The estimation results are presented with only variables that are significant on the 10% level or above (Table 3 and Table 4). In both Parking Choice Models and Interaction Models, OC is chosen to be the reference alternative.

4.1. Parking Choice Models

The model results demonstrated that all of the significant variables are identical for both modeling approaches. But it is observed that the parameter estimates of the ML model are generally larger than that of the CL model. Both models are fit well with a McFadden likelihood ratio index (LRI) of 0.3892 (>0.3).

In the ML model, all three parking lot attribute variables are significant, with p-values less than 0.0001, indicating that these factors significantly influenced parking choice behavior. The parameters of price and walking time are negative (Coefficient = -0.0439 and -0.0486, respectively), whereas the parameter of number of free hours is positive (0.1395), whose positive mark is consistent with the principles of parking choice psychology. Comparing these parameters, there is a significant difference in the order of magnitudes, in which the value for number of free hours is approximately three times of that of the other two parking lot attribute variables.

The estimations for Mid-income and Middle-age using underground parking (Mid-income & UG: 0.7730; Middle-age & UG: 0.6525) are slightly higher than using open-air parking (Mid-income & OA: 0.7262; Middle-age & OA: 0.4457), indicating that those in the mid-income and middle-age group were more likely to choose underground parking than open-air parking. Those who favored short-term and mid-term parking showed a highly significant tendency toward underground parking (Short-term & UG: -0.6363; Mid-term & UG: -0.1657). However, in social parking cases, underground parking always results in higher parking fees and longer walking times, while offering a more secure parking environment. Underground parking lots tend to provide a discount for long-term parking, whereas open-air parking lots do not. Hence, the utility of parking in underground lots is usually greater for long-term parking, which is the opposite trend to that for campus. In our setting, there was no difference in the walking times from underground and open-air parking lots, but the price of underground lots was much lower and the potential security level was obviously higher. Therefore, transferring the demand from open-air lots and curb parking to underground parking is feasible for campus parking.

4.2. Interaction models

The estimation results of the interaction models are shown in Table 4. Considering the LR value in the interaction models, the CL measure has an LR of 10,960 with 12 degrees of freedom, whereas the LR of the ML approach is larger (LR = 10,972) and has one more degree of freedom. In the ML model, two variables were tested as random parameters following a uniform distribution. The random parameters increased the goodness-of-fit of the model, indicating that heterogeneity must exist in this case. The McFadden LRI of the ML interaction model was 0.6665, which represents a better fit than the CL measure, for which the LRI was 0.6658.

The ML interaction model provides 12 parameters that are significant at the 0.1 level, seven of which are interaction terms with walking time. This result indicates that walking time had a much greater influence on parking choice than the other two parking lot variables, particularly when interacting with the respective individual variables. Among the individual variables, the estimated parameters of middle-age (Coefficient = -0.0338), teacher (1.3064), staff (1.3162) and mid-income (-0.0463) are significant at the 0.001 level, who were more sensitive to walking time than the other groups. In terms of occupation, staff and teachers were significantly more sensitive to walking time than the students. Middle-age drivers paid less attention to walking distance than others. Parking duration (-0.0138) and gender (0.0546) are the only two individual attribute variables that show a significant interaction with price. As the parking duration increases, a lower price is needed to cut down the total cost, which follows the basic principles of consumption psychology. Only the mid-term parking group was sensitive to the number of free hours (0.2329), with a significance level of 0.001. In commercial parking, drivers who expect to park for more than 3 hours seem to be less sensitive to the number of free hours. However, because the proportion of commuter parking is much larger than temporary parking on campuses, drivers show higher sensitivity to the number of free hours. Therefore, the average number of free hours in campus parking lots should be higher than in commercial lots.

Random parameters

As shown in Table 4, for the ML interaction model, the probability that the parameter of Walking Time & Gender is negative (Coefficient = -0.0584) is 72.4%, which means that in most cases, males are less sensitive to walking time. Similarly, for Walking Time & Mid-term, the probability that the parameter is less than 0 is 84.8%, with a negative coefficient of -0.3991. When interacted with the number of free hours, the parameter of mid-term parking is 0.2329, which indicates that the ML measure increased the overall significance level of people who parked for less than 8 h and more than 3 h. The younger age group, which is likely to be less concerned about walking time, is no longer among the significant variables. Nevertheless, walking time is still the most influential parking lot variable of the three. Gender and parking duration are still the only two variables that are influential when multiplied with price.

The alternative specific constants in these two approaches are all significant at the 0.001 level and have considerably large parameters (more than 20). This result is reasonable because the interaction model comprises only interaction terms and excludes the original characteristics. Therefore, the total explanatory ability of this model is much weaker than the parking choice model due to its lack of numerous predicative terms. The fundamental goal of this model is to determine the relationship between individual characteristics and parking lot attributes, and the heterogeneity of various individual groups.

4.3. Elasticity Analyses

Elasticity analyses are widely applied to determine the effect of each variable (Washington et al., 2012). The elasticity is calculated by partial derivative form as follows:

$$E_{x_{ki}}{}^{P(i)} = \frac{\partial P(i)}{\partial x_{ki}} \times \frac{x_{ki}}{P(i)} = [1 - P(i)]\beta_{ki} x_{ki} (x_{ki} \neq 0) \tag{6}$$

where $P(i)$ is the probability of alternative i being selected, x_{ki} is the value of variable k for alternative i and β_{ki} is the estimated parameter of x_{ki}. The elasticity value can be interpreted as the percentage change in probability $P(i)$ when x_{ki} changes by 1%. Note that elasticity is a point value when x_{ki} is given a specific value. If the elasticity of the indicator variables needs to be calculated, a pseudo-elasticity measure should be applied because the elasticity value is not applicable to variables that take values of 0 or 1 (Shaheed et al., 2013).

To compare the two modeling approaches, the elasticity values for the CL and ML models were computed and are listed in **Error! Reference source not found.**. For each parking lot attribute variable, the elasticity value changes regularly from open-air parking to off-campus parking lots. The elasticity values for price in both modeling measures remain nearly the same for open-air and off-campus parking and become the smallest for underground parking. The elasticity value of price is approximately four times higher for open-air or off-campus than for underground parking. This regulation implies that the users were less concerned about the price of underground parking than the price of the other two parking lots, which means that other aspects of underground parking such as the level of security and walking distance are considered to be more important. The elasticity values for walking time are almost the same for open-air and underground parking but are approximately eight times larger for off-campus parking lots. Obviously, parking off campus may increase walking time considerably, which greatly increases the elasticity value. The relatively distant off-campus parking lot locations also contribute to the large elasticity value because the sub-choice may lead to a 20-minute increase in walking time. In terms of the number of free hours, parking inside the Siping campus tends to result in fewer free hours, whereas when parking outside, users may park all day for free. Therefore, the elasticity for number of free hours is particularly different between open-air and off-campus parking.

Underground parking lots share similar elasticity regularity with off-campus parking lots for various parking lot attributes. For both types of parking, the highest elasticity value is for the number of free hours, followed by walking time, then price. However, considering the order of magnitude, the elasticity of price and walking time are almost the same for underground parking, but differ greatly for off-campus parking. Therefore, similar elasticity value regularities represent different 'relative elasticity' results (comparing the elasticity value with the value of the variable). For underground parking, the relative elasticity is almost the same for price and walking; however, for off-campus parking, because the value of walking time is many times higher than the value of price, the relative elasticity for price should be much greater than that for walking time. This means that people care more about price when considering off-campus parking lots because all of these parking lots require extremely long walking times. For the open-air parking lots on-campus, the elasticity values for number of free hours is the largest, followed by price and walking time. Considering the order of magnitude of the various variables, price has larger relative elasticity than walking time for off-campus parking. This results from the limited area of Siping campus, which leads to the lack of elasticity in walking time.

Comparing the elasticity values calculated from the CL and ML models, it is obvious that the absolute values in the ML model are larger. This proves that the ML model can release the IIA limit and become more interpretive. Further, among all of the elasticity values, the one for the number of free hours for off-campus parking is the largest and is greater than 1 (1.34 for the CL model and 2.13 for the ML model). This is a consequence of the order of magnitude of the variables.

4.4. Area comparison

To access the role in decision making of the large underground parking lot being constructed, ML parking choice models for both Area A and B were established and analyzed (Table 6).

The parking choice model shows that number of free hours is a major contributory factor for both Area A (Coefficient for Area A = 0.1932) and B (0.4312), at a 1% significant. On the other hand, walking time is significant at the 0.001 level for Area B (-0.0767) only, which indicates that decision makers in Area B cared more about walking distance than those in Area A. Different from the overall parking choice model, price is not a major consideration for drivers in Area A and B.

For the individual characteristics, it was found that four variables in Area A show significant interactions with underground parking, including mid-income middle-age (Middle-age & UG: -0.6244), parking duration (Short-term & UG: -1.5638; Mid-term & UG: -0.7130) and teacher (Teacher & UG: -0.5585). All of the parameters of these four variables are less than zero, which means that the probability of people with these four characteristics parking in underground lots is relatively low. Similarly, drivers belong to the mid-income (Mid-income & OA: -0.1484), middle-age (Middle-age & OA: -0.2851) and short-term parking (Short-term & OA: -1.2514) also have a negative interaction with open-air parking, and hence drivers from these groups are less likely to park in an open-air parking. Different from Area A, no interaction was found between the individual characteristics and underground parking. On the other hand, it was found that drivers with mid-income are likely to use the open-air parking (Mid-income & OA: 1.1408) and underground parking (Mid-income & UG: 1.0113). Furthermore, teachers in this area also demonstrated a positive interaction with open-air parking (Teacher & OA: 2.8994). Interestingly, off-campus parking is a favorable parking choice for mid-term parking (Mid-term & OC: 2.8136) in Area B.

Random parameters

The variables that show heterogeneity are number of free hours for both areas and Teacher & OA for Area B. There is a difference in heterogeneity in teachers' attitudes toward open-air parking. The probability of this parameter being greater than 0, calculated from a uniform distribution between (-1, 1) is 100%, which means that in general, the teachers in Area B indicated a significant preference for parking inside the campus, but the preference was expressed at different levels. The difference in attitudes toward parking in the open-air areas may result from the different walking distances to underground parking lots between the two areas: the imbalanced distribution of the underground lots in Area B increases the willingness of the drivers to park in the open air.

5. Conclusions

University campuses have a semi-isolated transportation network with specific transport problems, which can severely influence the surrounding neighborhood. Although the concept of TDM has started to be applied in campus parking management, the heterogeneous characteristics of people parking on university campuses has rarely been considered. This study proposes an ML modeling approach with interaction terms to model special parking behavior in university campuses considering the preferences of various user groups.

A case study in Siping Campus, Tongji University, Shanghai, China, was conducted to assess the performance of the modeling framework. The preferences of parking space users on the Siping campus were surveyed using SP questionnaires. Three hypothetical scenarios were provided: open-air, underground and off-campus parking lots. Through primary statistical analyses, the parking preferences of the teachers, staff and students were identified, together with the major variables that influenced parking behaviors. The results of this study demonstrated that the parking lot factors (including 2 specific constants, price, walking time and number of free hours) were all influential in the context of the parking choice models. The strong preference for underground parking on campus should facilitate campus parking management to set up vertical parking policies. Moreover, heterogeneity among individuals with different demographic and parking characteristics was found in campus parking choice modeling. In the interaction models, individual characteristics and alternative specific attributes were interacted as independent variables and all other terms except for the parking lot constants were removed from the model. The interaction models showed that walking time strongly influenced people with different characteristics, and should therefore be considered the most important parking lot variable in campus parking management. Mid-term parking and gender, the parameters of which were random when interacted with walking time, improved the goodness-of-fit and LR results of the ML model much more than those of the CL model. Heterogeneity was quantified by assuming that the parameters followed a uniform distribution.

In the elasticity analyses, stable regularity was found in every direction. The elasticity value of the number of free hours was larger than for the other parking lot variables and can be considered as having full elasticity. Further, the elasticity values of the ML model were larger and the model was shown to be free from the IIA limitation.

5.1. *Parking policy implications in Tongji University*

To systematically manage parking issues in Tongji University, separated ML parking choice models were developed for the two campus areas in Siping Campus of Tongji University. It was found that 1) drivers who work (or study) in Area B, which is located farther from the proposed parking lot than Area A, care more about walking distance; and 2) drivers in Area A indicated a greater unwillingness to park in underground lots. Despite this, both findings indicate resistance to parking in the new underground parking lot. In this regard, distinctive parking policies for various parking locations should be adopted after the large underground parking lot is finished.

To systematically manage parking issues in Tongji University, several suggestions on policy making are provided:

(1) Walking time should be given great consideration when devising the parking fee scheme because it was proved to be the most significant attribute in both of the parking choice model and the interaction model.

(2) The number of free hours should be set higher than that in commercial parking lots because this is a much more important requirement for commuters than for temporary commercial parking.

(3) The duration of free parking in open-air parking lots of area A can be set lower than in other lots to encourage drivers to use the underground parking lot.

(4) A smaller increase in the duration of free parking in the underground parking lot than the proposed raise in ((3) would offset the unwillingness of people in area B to walk long distances while maintaining the available parking supply in area A.

(5) Teachers should be offered a subsidy to park in the new underground parking lot.

5.2. Limitations of this study

The random parameter ML model is one of the most common measures for quantifying heterogeneity in discrete choice behavior. The high significance levels and the relatively large number of choice-specific constants in the models illustrate that some hidden properties may influence parking choice behavior on campuses, and it might be of value to explore and model these properties, such as environmental characteristics and some traffic management measures. Because of the limited sample size and the properties of real-world situations, the number of variables and alternatives had to be carefully selected, which meant that some other important factors (such as traffic conditions during parking searches) and other possible alternatives (such as splitting open-air parking into curbside and open parking lots) could not be considered. A detailed parking policy scheme for managing campus parking demand should be settled on after further enrichment of the survey and modeling process.

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Table 1. Summary of Attribute Levels in the SP Experiment

	Alternative	Price (CNY/h[a])	Walking time (min)	Number of free hours (h)
Scenario 1	OA	3	5	24
	UG	0	5	24
	OC	0	15	24
Scenario 2	OA	3	8	6
	UG	0	5	24
	OC	0	15	24
Scenario 3	OA	4	1	4
	UG	0	5	24
	OC	0	15	24
Scenario 4	OA	2	1	4
	UG	4	5	10
	OC	0	15	24

OA: Open-air parking; UG: Underground parking; OC: Off-campus parking.
a. CNY is the official unit of currency in China: 1 CNY=0.161 USD.

Table 2. Summary of Explanatory Variables

Category	Explanatory variable	Description	Mean	SD
(a) Parking lot attributes	Specific constant for OA	1=on-campus parking, 0=else	-	-
	Specific constant for UG	1=underground parking, 0=else	-	-
	Price	Continuous variable, unit: CNY/h	1.65	1.96
	Walking time	Continuous variable, unit: min	12.74	5.81
	Number of free hours	The number of the first several hours in which parking is free of charge. Continuous variable, unit: h	17.20	4.69
(b) Individual characteristics	Gender	1=male, 0=female	0.60	0.49
	Age			
	- Youth	1=15<age≤30, 0=else	0.07	0.25
	- Middle-age	1=30<age≤55, 0=else	0.73	0.45
	Occupation			
	- Teacher	1=teacher, 0=else	0.68	0.47
	- Staff	1=executive staff, 0=else	0.32	0.47
	- Student	Control level	-	-
	Income			
	- High-income	1=income≧20000CNY, 0=else	0.02	0.14
	- Mid-income	1=10000CNY≤income<20000CNY, 0=else	0.57	0.50
	- Low-income	Control level	-	-
	Daily parking duration			
	- Short-term	1=daily parking duration ≤3 h, 0=else	0.09	0.28

-	Mid-term	1=3 h<daily parking duration≤8 h, 0=else	0.32	0.47
-	Long-term	Control level	-	-

OA: Open-air parking; UG: Underground parking.
SD: Standard deviation

Table 3. Modeling Results of Parking Choice

Variable	Conditional logit		Mixed logit	
	Coefficient	Pr>|t|	Coefficient	Pr>|t|
(a) Parking lot attributes				
Specific constant for OA	3.0564***	<.0001	3.1160***	<.0001
Specific constant for UG	2.2233***	<.0001	2.2814***	<.0001
Price	-0.0439***	<.0001	-0.0439***	<.0001
Walking time	-0.0487***	<.0001	-0.0486***	<.0001
Number of free hours	0.1395***	<.0001	0.1395***	<.0001
(b) Individual characteristics				
Mid-income & OA	0.7855***	<.0001	0.7262***	0.0002
Mid-income & UG	0.8315***	<.0001	0.7730***	<.0001
Middle-age & OA	0.4651*	0.0514	0.4457*	0.0670
Middle-age & UG	0.6718**	0.0044	0.6525**	0.0066
Short-term & UG	-0.6317***	<.0001	-0.6363***	<.0001
Short-term & OC	-0.5886***	<.0001	-0.5919***	<.0001
Mid-term & UG	-0.1657**	0.0068	-0.1657**	0.0090
Teacher & OC	0.3289**	0.0076	0.3294*	0.0140
Number of observations	7,492		7,492	
Likelihood ratio	6,406		6,406	
McFadden LRI	0.3892		0.3892	

OA = Open-air parking; UG = Underground parking; OC = Off-campus parking.
LRI = Likelihood ratio index.
* = significant at 10%; ** = significant at 5%; *** = significant at 1%.

Table 4. Estimation Results for Interaction Models

Variable	Conditional logit		Mixed logit	
	Coefficient	Pr>|t|	Coefficient	Pr>|t|
Specific constant for OA	24.2184***	<.0001	24.8422***	<.0001
Specific constant for UG	21.0686***	<.0001	21.8972***	<.0001
Price & Gender	0.0561**	0.0010	0.0546**	0.0032
Price & Parking duration	-0.0150***	0.0002	-0.0138***	<.0001
Walking Time & Gender	-0.0317**	0.0092	-0.0584**	0.0188
(scale)			(-0.1303*)	(0.0416)
Walking Time & Youth	-0.0417*	0.0846	-	-
Walking Time & Middle-age	-0.0613***	<.0001	-0.0338*	0.0665
Walking Time & Teacher	1.2646***	<.0001	1.3064***	<.0001

Walking Time & Staff	1.2826***	<.0001	1.3162***	<.0001
Walking Time & Mid-income	-0.0422***	0.0005	-0.0463**	0.0040
Walking Time & Mid-term (scale)	-0.0358*	0.0202	-0.3991*** (0.5733***)	<.0001 (<.0001)
Number of free hours & Mid-term	0.0353**	0.0093	0.2329***	<.0001
Number of Observations	7,492		7,492	
Likelihood Ratio	10,960		10,972	
McFadden LRI	0.6658		0.6665	

OA = Open-air parking; UG = Underground parking.
LRI = Likelihood ratio index.
* = significant at 10%; ** = significant at 5%; *** = significant at 1%.

Table 5. Elasticity of Parking Lot Attribute Variables

Variable	Conditional logit			Mixed logit		
	OA	UG	OC	OA	UG	OC
Price	-0.07397	-0.02186	-0.07362	-0.1636	-0.04836	-0.1626
Walking time	-0.05078	-0.05986	-0.40319	-0.06058	-0.07144	-0.48042
Number of free hours	0.25322	0.39752	1.33878	0.40287	0.63263	2.12712

OA = Open-air parking; UG = Underground parking; OC = Off-campus parking.

Table 6. Estimation Results for Parking Choice Models in Area A and Area B

Variable	Area A		Area B	
	Coefficient	Pr>|t|	Coefficient	Pr>|t|
(a) Parking lot attributes				
Specific constant for OA	0.4601***	0.0002	3.3449***	<.0001
Specific constant for UG	-3.2323***	<.0001	-	-
Walking time	-	-	-0.0767***	<.0001
Number of free hours	0.1932***	<.0001	0.4312***	<.0001
(scale)	(0.2333***)	(0.0004)	(-0.5759*)	(0.0244)
(b) Individual characteristics				
Mid-income & OA	-0.1484*	0.0811	1.1408***	0.0003
Mid-income & UG	-	-	1.0113***	0.0008
Middle-age & OA	-0.2851**	0.0015	-	-
Middle-age & UG	-0.6244*	0.0192	-	-
Short-term & OA	-1.2514***	<.0001	-	-
Short-term & UG	-1.5638**	0.0065	-	-
Mid-term & UG	-0.7130*	0.0147	-	-
Mid-term & OC	-	-	2.8136***	<.0001
Teacher & OA (scale)	-	-	2.8994*** (2.3141***)	<.0001 (0.0001)

Teacher & UG	-0.5585***	<.0001	-
Number of observations	7492		7492
Likelihood ratio	3453		3021
McFadden LRI	0.3918		0.3950

OA = Open-air parking; UG = Underground parking; OC = Off-campus parking.
LRI = Likelihood ratio index.
* = significant at 10%; ** = significant at 5%; *** = significant at 1%.

Figure 1. Parking arrangement in Siping campus of Tongji University