



A Spatial Hazard-Based analysis for modelling vehicle selection in station-based carsharing systems



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ABSTRACT

Carsharing, as an alternative to private vehicle ownership, has spread worldwide in recent years due to its potential of reducing congestion, improving auto utilization rate and limiting the environmental impact of emissions release. To determine the most efficient allocation of resources within a carsharing program, it is critical to understand what factors affect the users' behavior when selecting vehicles. This study attempts to investigate the importance of users' attributes and fleet characteristics on choice set formation behavior in selecting vehicles using a Spatial Hazard Based Model (SHBM). In the SHBM model, "distance to a vehicle" is considered as the prospective decision criteria that carsharing users follow when evaluating the set of alternative vehicles. This variable is analogous to the duration in a conventional hazard-based model. In addition, user socio-demographic attributes, vehicle characteristics, land use type of the trip origin, etc., collected from the Australian carsharing company GoGet are utilized to parameterize the shape/scale/location parameter of the hazard function. A number of forms of parametric SHBMs are tested to determine the best fit to the data. The accelerated failure time model with a Log-logistic distribution was found to provide the best fit. The estimation results of the coefficients of the parameters can provide a starting point for carsharing organizations to optimize their pod locations and types of cars available at different pods to maximize usage.

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1. Introduction

In recent times, transportation planning has focused on the concept of sustainability. The goal of a majority of transport planning practices is ensuring a livable community for the current generation whilst considering the impact on future generations. A number of transportation authorities have recognized that private car ownership has significant costs associated to individuals and transport authorities in relation to purchase and maintenance costs as well as the provision of infrastructure (Duncan, 2011). In addition, increased private vehicle use has resulted in traffic congestion. Some of the repercussions due to traffic congestion include excessive delay, increased fuel consumption, greater road infrastructure costs and higher levels of emissions reducing air quality, which has resulted in significant economic and social costs (Wijayarathna, 2013; Banister, 2005; Catalano et al., 2008). In order to mitigate congestion, planners have advocated the development and use of public transit, carpooling, walking and cycling. Carsharing schemes, a form of short-term car rental, have become a

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complement to the previously mentioned sustainable transport approaches. Since its inception in the 1980s, carsharing schemes have become a crucial element of sustainable transport systems within the modern urban cityscape.

Studies have shown that carsharing scheme has the advantage to reduce the number of vehicles required to meet the total travel demand (Barth and Todd, 1999). Further, it has the potential to reduce congestion, provide more equitable access to private transport and limit the environmental impact of emissions release (Duncan, 2011). These advantages have resulted in an increasing development of carsharing programs as a mode of transport in planning for a sustainable transportation system. Thus, it is critical to understand what factors affect the demand for carsharing to further their usage. Demand is dependent on trip attributes such as: trip purpose, duration of the trip, time of day and week and also the vehicle selected out of the available choices. Jorge and Correia (2013) presented a comprehensive literature review regarding demand modelling approaches for carsharing programs. The paper highlighted that demand estimation is difficult due to the interdependency of vehicle availability and the number of trips. Furthermore, there has been limited research into understanding and characterizing the supply within modelling frameworks. In order to evaluate carsharing programs effectively, the demand for and the supply provided must be accurately determined. With respect to the supply of vehicles, carsharing programs can be categorized into free-floating and station-based systems based on facility configuration. Free-floating systems allow users to pick up and drop off a car freely in a defined zone without any fixed positioning. Station-based systems provide users with multiple predefined “pick up and drop off” vehicle pods (Firnkorner and Müller, 2011), which can be further classified into round-trip and one-way trip carsharing systems based on trip configuration. Station-based systems are less flexible for the consumer but more widely adopted by carshare operators. This study focuses on station-based carsharing systems and aims to advance the existing literature by investigating users’ vehicle selection behavior which is constrained by the supply of vehicles within station-based carsharing facilities.

Users’ vehicle selection is a significant factor in determining the most efficient allocation of resources within a carsharing program. Vehicle selection is the decision process undertaken by an individual to select a specific vehicle given a choice of vehicles within a carshare fleet. By understanding vehicle selection, programs can optimize the vehicle utilization within the fleet. Thus, this study attempts to answer two questions: “How far is an acceptable walking distance when users make decision on using carshare vehicles?” and “What factors influence users’ selection of vehicles?” Since the choice set of carshare vehicles is very large, users will follow two steps to make the decision. First users screen the alternative and come up with a small and manageable choice set and second they make their selection from options considered in the choice set. The paper attempts to present a method for the first step while the second step in which advanced discrete choice models will be used in undergo as the next step of this paper. Users’ cognitive capacity for screening and filtering alternatives from a choice set based on a critical or influential factors is an essential component of first step of vehicle selection behavior (Rashidi and Mohammadian, 2012). Accessibility to carsharing facilities dictates the utilization of carsharing facilities. Thus, the main factor affecting the choice set of vehicles is considered to be the “distance to the carsharing vehicle within a specific carsharing facility”. A Spatial Hazard Based Model (SHBM) has been formulated using data provided by GoGet, an Australian carsharing company. The SHBM is applied instead of a discrete choice model since it is more consistent with users’ vehicle selection process than discrete choice models. The modelling was achieved by considering “distance to the carsharing vehicle” as a random variable analogous to the duration in conventional HBMs. A number of parametric forms of HBM were tested to determine the best fit to the data set. The two major contributions of this study are: (1) introducing an analytical modelling structure for modelling demand for carsharing with a focus on vehicle selection and (2) application of a choice set formation technique that has been previously applied to a housing search problem (Rashidi and Mohammadian, 2012).

The remainder of the paper has been structured in the following manner. Section 2 provides a detailed literature review discussing the recent studies within carsharing demand modelling and the application of HBMs within the field. The collection and preparation of the data sets used to formulate the model are discussed in Section 3. The modelling framework and analysis methodology of the spatial hazard based model is then explained within Section 4. This is followed by Section 5 which presents the results and analysis of the modelling. Finally, the implications of the results and future research surrounding this topic are highlighted within Section 6.

2. Literature review

The history and development of carsharing programs provide a source of motivation for this investigation. In terms of transport planning, carsharing program is a travel demand optimization strategy. Carsharing offers the user the choice to forego ownership of a vehicle as he or she will still have access to a private vehicle when it is absolutely necessary for specific trip purposes, as a result this has the potential to reduce the number of vehicles travelling within the overall network. Martin et al. (2010) studied the impact of carsharing on household vehicle holdings in North America and presented that the average number of vehicles per household dropped from 0.47 to 0.24 for households which utilize carsharing. Furthermore, the analysis suggests that carsharing has removed 90,000–130,000 vehicles from the road at an aggregate level. The latest three-year study on one-way carsharing services of five major cities in North America also demonstrated the mileage reduced by carsharing has exceeded the mileage created by it, resulting in a decrease in annual vehicle mileage by 10–29 million miles per city investigated (Martin and Shaheen, 2016). A vast amount of literature has highlighted the advantages of carsharing programs (Shaheen et al., 1998; Stillwater et al., 2009; Duncan, 2011; Jorge and Correia, 2013; Shaheen and Cohen, 2013). For

further information about carsharing, [Shaheen and Cohen \(2013\)](#) provided the latest overview of the state of practice of carsharing and its impact on transportation systems. The main advantages can be summarized as follows:

- Reduction in travel costs to a user: Carsharing provides an option to reduce the fixed costs associated with car ownership, such as, insurance, registration and service costs ([Katzev, 2003](#)). Thus at an individual user level it can encourage saving and more efficiently allocate income.
- Improved accessibility to private vehicle usage: Socially sustainable transport systems can be achieved as lower income earners can now potentially access private vehicles whereas without carsharing schemes it would not be financially feasible ([Wachs and Taylor, 1998](#)).
- Alleviation in traffic congestion: As mentioned before, carsharing reduces the need for private vehicle ownership which in turn reduces the number of vehicles traversing the network and consequently decreases the vehicle kilometers travelled ([Martin et al., 2010](#); [Shaheen and Cohen, 2013](#)). Currently, this advantage can be enhanced with the advent of autonomous vehicles. As studied by [Fagnant and Kockelman \(2014\)](#), each shared autonomous vehicle can replace around eleven conventional vehicles owing to its potential to overcome carsharing barriers regarding to users' travel to access available vehicles.
- Reduction in release of emissions limiting the environmental impact of private vehicle usage.
- Improved parking conditions as a reduction in car ownership will reduce the demand for off and on street parking of private vehicles.

Literature suggests the need for carsharing as a mode of transport within the urban environment ([Stillwater et al., 2009](#); [Cari et al., 2013](#); [Jorge and Correia, 2013](#); [Shaheen and Cohen, 2013](#)). However the efficient and effective implementation of the programs is essential for the future success of carsharing and as a result a number of studies ([Catalano et al., 2008](#); [de Almeida Correia and Antunes, 2012](#); [Morency et al., 2012](#); [Cari et al., 2013](#); [Schmöller et al., 2015](#); [Jorge et al., 2015](#)) have been conducted to understand what factors determine the demand and supply for carsharing. This study adds to the growing body of literature by providing a greater understanding of a users' vehicle selection attributes within a carsharing scheme.

User behavior modelling is one of the branches of carsharing that has recently attracted some attention. Most studies have adopted regression models, stated-preference surveys and data mining techniques to study the characteristics of users of carsharing programs ([Catalano et al., 2008](#); [Stillwater et al., 2009](#); [Morency et al., 2011](#); [Schmöller et al., 2015](#); [Jorge et al., 2015](#)). [Catalano et al. \(2008\)](#) conducted a stated preference survey within the city of Palermo in Italy. Using the data from 500 respondents the study develops a random utility model and tests future carsharing policy scenarios highlighting volatility in carsharing usage across the scenarios tested. [Stillwater et al. \(2009\)](#), on the other hand, conducted a GIS-based multivariate regression analysis to understand the impact of the built environment and demographic factors of users' on carsharing demand. Sixteen months of usage data from a carsharing operator in the U.S. were used to conduct the analysis which suggested that single vehicle households, the availability of light rail facilities and the age of the carshare pod had a positive relationship with demand for carsharing. [Morency et al. \(2011\)](#) advanced this stream of research by establishing the typology of carsharing users using the carsharing transaction data provided by Communauto, a carsharing company in Montreal, Quebec. The authors used data mining techniques to categorize members based on their temporal units that represented their behavior. The results indicate a greater proportion of low frequency users (on average 0.4 uses of the program per week) and as a result lower distances travelled (14.3 km per week) which is consistent with the aims of the short-term rental principle of carsharing.

More recently, [De Lorimier and El-Geneidy \(2013\)](#) developed a multilevel regression model to determine the factors that affect vehicle usage and used a logistics regression analysis to analyze the carsharing vehicle availability. The data used in this research also came from Communauto, a carsharing company in Canada. The results showed that the size of a carsharing station was a key factor to vehicle usage. [Morency et al. \(2012\)](#) continued investigating the data of Communauto and proposed a two-stage approach to estimate the frequency of usage by an active member. The first stage involved the development of a binary probit model to understand the probability that a member will be active and the second stage was a random utility based model which estimated the probability that a customer will use carsharing more than once per month given they are an active member. The results indicated that recent usage had a positive relationship with the likelihood of future use. However, it is heavily dependent on demographic factors such as age and language spoken at home.

[Schaefers \(2013\)](#) explored carsharing usage motives using a qualitative means-end chain analysis. They collected data through a series of laddering interviews attended by members of a carsharing company in U.S. The interviews followed the hierarchical structure of means-end chain method. The authors created a hierarchical value map (HVM) to describe the relationships between carsharing attributes and users' core values. They concluded that there are four motivational patterns in carsharing context, namely value-seeking, convenience, lifestyle, and environmental consciousness. The results of this study could be used in making targeted carsharing development strategies.

In the context of vehicle selection and supply, [Schmöller et al. \(2015\)](#) completed an empirical study on the spatial and temporal utilization of 'free-floating carsharing' within Munich and Berlin (Germany). As mentioned earlier, free-floating carsharing programs do not require vehicle pods/stations and allows for one-way trips. Though this differs from traditional, station-based carsharing and the focus of this paper, the analysis of the booking data revealed asymmetries in the spatiotemporal distribution of vehicle supply and demand and suggested the demand for the service can be influenced by both short-term and long-term factors. Regarding to the supply-demand asymmetry problem raised in such one-way carsharing

programs, [Weikl and Bogenberger \(2015\)](#) proposed a relocation model to optimally relocate vehicles to balance vehicle supply distribution. [Cepolina and Farina \(2012\)](#) also developed a fleet optimization algorithm to optimize the fleet dimension and its distribution among stations in one-way carsharing systems. [Correia et al. \(2014\)](#) considered the flexibility of user's choice on carshare stations: users might not always select the closest carshare station, instead they might use the second or even the third closest station if there was no vehicle available in the closest station. Their findings reflected the impact of the information of station vehicle stocks on user's station choice, and implied the complexity of users' vehicle selection process. Furthermore, [Schmöller et al. \(2015\)](#) provided insight into data analysis techniques used to study the spatial relationship with vehicle booking of a carsharing program, which closely aligns with the work carried out within this study. Although the aforementioned studies provide a thorough understanding of some of the significant factors that affect carsharing user behavior, to the authors' best of knowledge, the process of vehicle selection by a user, in the context of station-based carsharing, has yet to be fully investigated.

Recently, some studies have utilized hazard based modelling techniques to explore users' behavior within carsharing programs ([Habib et al., 2012](#); [Morency et al., 2012](#)). [Habib et al. \(2012\)](#) further utilized the data provided by Communauto to present a discrete time hazard model to estimate membership continuation of users. Similarly, [Costain et al. \(2012\)](#) also applied hazard model to investigate membership duration of carsharing users. The study initially carried out descriptive analysis to investigate key attributes that influence the overall patterns of users' behavior. Subsequently, the authors developed several econometric models, including a binary logit model, a hazard model, a negative binomial model, a multivariate regression model, and a multinomial logit model. These models were used to analyze a number of factors including users' attitude towards environment and safety, frequency of usage and vehicle type choice. Among these models, the hazard model was employed to model membership duration. The results revealed that higher monthly rate and less perceived saving would shorten membership duration. The methodology underpinning these studies provided guidance in developing a model which focuses on vehicle selection, as this is a discrete decision made based on a set of given alternatives.

The behavior of vehicle selection is a discrete choice for an individual when utilizing carsharing. A user needs to select a single vehicle out of a choice set and how we define the choice set is an important consideration and a key focus of the study. Literature has shown that choice set formation has an impact on the parameter estimation of behavioral choice models ([Ben-Akiva and Lerman, 1985](#); [Timmermans and Golledge, 1990](#); [Rashidi and Mohammadian, 2012](#)). [Rashidi and Mohammadian \(2012\)](#) presented a detailed review of approaches to choice set formation which has historically been classified into two approaches: random selection out of the universal choice set and consideration of the entire universal choice set, both containing weaknesses in developing accurate behavioral models. In addition, the most critical element within choice set formation is developing an appropriate filtering/screening method ([Rashidi and Mohammadian, 2012](#); [Manski, 1977](#)). The decision process can be completed in two phases: initially the hazard model determines a filtered choice set identifying the probabilistically relevant alternatives and then a secondary choice model determines the alternative with the greatest utility from this filtered choice set ([Rashidi and Mohammadian, 2012](#)). The study presented within this paper attempts to achieve the first step of this process through the use of a Spatial Hazard Based Model (SHBM), a relatively new technique that has had a few applications within literature ([Rashidi and Mohammadian, 2012](#); [Rogerson et al., 1993](#); [Pellegrini and Grant, 1999](#)). The model considers "distance to the carsharing vehicle" as a random variable analogous to the duration of a HBM to construct the choice set of the vehicle selection decision.

3. Data collection and preparation

GoGet, an Australian carsharing company founded in 2003 operating throughout Sydney, Melbourne, Brisbane and Adelaide graciously provided the data set used to undertake this research. Anonymous carsharing trip data of the Sydney region obtained between January 1st, 2012 and June 9th, 2012 was utilized for the development of the SHBM. At the time of data collection, GoGet operated round-trip station-based carsharing services, and there were 55 GoGet vehicle pods (carsharing facilities) located in Sydney containing a total of 208 vehicles. The recorded data considers 23,642 trips completed by 3081 users across the six-month period of data collection. The data set includes a wide range of anonymous user-related, vehicle-related, and trip-related variables, which are described in [Table 1](#). These variables are selected specific to the aims of the research: understanding the vehicle selection within carsharing programs.

User-level variables (variable ID 1–9 shown in [Table 1](#)) were extracted directly from the anonymous user information provided by GoGet. Information regarding the users' age, car ownership and usage and journey to work were obtained. Eight out of the nine user level variables were binary in nature. The variable *user_landuse_binary* identifies if the land use of the origin is residential or not. This classification is based on the land use zoning map obtained from the NSW Department of Premier and Cabinet, Office of Environment and Heritage ([NSW GOVERNMENT ENVIRONMENT AND HERITAGE, 2014](#)). Among all the users, 67.87% are originating from residential areas, 25.12% from commercial or industrial areas, and 7.01% from public services or recreational area. The variable *user_live_dedicated_parking* is extracted from the survey responses conducted by GoGet. The variable captures whether a member believes that they have a dedicated parking spot near them.

The variable *plan_binary* divides users into frequent user group and infrequent user group. At the time of data collection, GoGet provided five membership plans to users with different monthly rates and trip rates: GoFrequent, GoOccasional, GoS-tarter, GoBusiness, and GoStudent. The variable *plan_binary* equal to 1 indicating the user is on GoFrequent plan. It has the

Table 1
Summary of the variables used in the models.

	ID	Variable	Mean	Std. dev.	Percentage of binary variable = 1	Definition
User	1	User_age (year)	39.60	10.86	–	Age of user
	2	User_car_ownership	–	–	20.90	Binary variable: =1, user owns a car; =0, otherwise
	3	User_how_often_use_the_car	–	–	34.79	Binary variable: =1, user uses the car at least once a week; =0, user rarely uses the car, i.e. less than once a week.
	4	User_main_way_to_work	–	–	58.33	Binary variable: =1, user uses public transit to work; =0, otherwise
	5	User_landuse_binary	–	–	67.87	Binary variable: =1, user's origin landuse type is residential; =0, otherwise
	6	User_live_near_dedicated_parking	–	–	70.11	Binary variable: =1, user lives near dedicated parking pod; =0, otherwise
	7	DI_country	–	–	79.10	Binary variable: =1, user's driving license country is Australia; =0, otherwise
	8	Plan_binary	–	–	26.74	Binary variable: =1, user owns a frequent usage membership plan; =0, otherwise
	9	Booking_method	–	–	11.46	Binary variable: =1, user uses mobile phone to book a car; =0, otherwise
Vehicle	10	Car_manufacture	–	–	11.55	Binary variable: =1, the manufacturer of the car is Alfa Romeo, =0, otherwise
	11	Car_body_type	–	–	18.86	Binary variable: =1, the car is MPV or Electric vehicle; =0, the car is hatchback
	12	Car_age (year)	3.30	0.74	–	Age of GoGet car
	13	Pet_friendly	–	–	7.82	Binary variable: =1, the car is pet friendly; =0, otherwise
Trip	14	Trip_travel_time (hours)	0.21	0.55	–	Total travel time of each trip
	15	Usage	3.07	10.04	–	Number of times user has used a vehicle

lowest trip rate and the highest monthly service subscription rate. It is more suitable for users using carsharing service frequently.

Vehicle-related variables include the manufacturer, body type, age, and pet option of the vehicles. Four manufacturers, Toyota, Hyundai, Alfa Romeo and Suzuki, supply the fleet of 208 GoGet vehicles being studied. The trip rate, i.e. the rate GoGet charges users per hour and per kilometer, of these cars are different. Out of all the manufacturers, the carsharing rate charged for using Alfa Romeo vehicles is the highest as this is deemed to be a luxury vehicle. The other manufacturers have equal rate and the hourly rate is AU\$2 (AU\$1 = US\$0.75 [29/08/2016]) lower than the rate of Alfa Romeo. As a result, a *car_manufacture* variable is generated as a binary variable that if the manufacturer is Alfa Romeo it equals 1, and 0, otherwise. The variable *pet_friendly* identifies whether the vehicle is pet friendly. Trip-level attributes consist of trip travel time and the number of times that each user selects each car, denoted by *usage*.

Table 2 presents the correlation between the 15 variables. Though a majority of the coefficients are less than 0.15, there are several correlations that should be noted. Variable *user_how_often_use_the_car* (3) and *plan_binary* (8) have a weakly positive correlation of 0.22 indicating that frequent carshare users tend to also be private vehicle users. The variable *car_body_type* (11) are negatively correlated with *car_manufacture* (10), *car_age* (12) and *pet_friendly* (13). This shows that vehicles with special body types are mostly older vehicles and not pet-friendly compared to hatchbacks.

Table 2
Correlation between Variables.

ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1.00														
2	0.11	1.00													
3	0.06	0.10	1.00												
4	−0.02	−0.06	−0.07	1.00											
5	−0.15	0.07	0.08	0.04	1.00										
6	−0.05	0.06	−0.05	0.07	−0.03	1.00									
7	0.15	0.13	0.04	−0.01	0.01	−0.06	1.00								
8	0.11	−0.04	0.22	0.00	−0.12	−0.07	0.02	1.00							
9	−0.11	−0.04	0.05	0.00	0.01	0.03	0.00	0.14	1.00						
10	0.01	0.01	0.01	0.00	0.00	−0.01	0.01	0.00	0.00	1.00					
11	−0.01	0.01	−0.01	−0.02	−0.02	0.00	0.00	0.00	0.00	−0.22	1.00				
12	0.00	0.03	0.02	0.00	0.01	0.01	0.02	0.00	−0.01	−0.11	−0.21	1.00			
13	−0.01	0.00	−0.01	0.00	−0.01	−0.01	0.01	0.02	0.01	−0.16	−0.20	−0.09	1.00		
14	0.02	0.01	−0.02	−0.01	−0.02	0.01	−0.03	−0.01	−0.01	0.00	−0.01	−0.01	0.00	1.00	
15	0.01	−0.03	0.05	0.04	0.03	−0.03	0.02	0.01	0.02	−0.09	−0.14	−0.06	−0.11	−0.03	1.00

GoGet provided the Euclidean distance between a user’s residence and carshare vehicle pod. Furthermore, it is also important to note, a maximum travel distance catchment of two kilometers that an individual would travel to a vehicle pod was assumed within this study. This assumption was made to complete an initial screening of the data to determine feasible travel distances between the origin and the vehicle pod as walking is the dominant access/egress mode to GoGet vehicles. Thus, the application of Euclidean distance offered a reasonable estimate for distances less than 2 km. Fig. 1 presents a distribution of the observed GoGet usage data considering the two-kilometer origin to vehicle pod radius. The figure shows a high proportion of users located within one kilometer of the vehicle pod (62% of the total data set) with the usage decreasing as the distance increases. In addition, the total catchment considers 80% of the data set. Accordingly, the use of the two-kilometer catchment was deemed as a valid initial screening criterion to obtain realistic modelling.

In addition, the GoGet booking system only provides users information regarding available vehicles when booking. Thus, within the modelling framework, it is assumed that the user can only select vehicles that are available at the time of utilization narrowing the choice set.

4. Model formulation and methodology

The parametric hazard based models used in this study are introduced in this section. To begin with the various types of parametric models are introduced and this is followed by a presentation of the constraints related to the problem, and finally the criteria of selecting among a set of parametric models.

In the area of survival analysis, there are two categories of parametric models, namely the accelerated failure time model (AFT model) and the proportional hazards model (PH model) (Rashidi and Mohammadian, 2015). The AFT model considers a linear relationship between the log of survival time and the covariates considered, while a proportional hazard model assumes that absolute differences in covariates imply proportionate differences in the hazard rate at a specific time. There are different probability distributions, such as exponential distribution, Weibull distribution and log-logistic distribution, employed to formulate parametric hazard models (i.e. both AFT and PH). Among these distributions, the Weibull function has been most frequently used in the studies of duration modelling (Yamamoto and Kitamura, 2000; Rashidi and Mohammadian, 2012; Hasan et al., 2013; Haque and Washington, 2015) since Cox (1959) first proposed the Weibull baseline hazard model. It presents a flexible functional form that can capture monotonically increasing or decreasing hazard function. However, it should be noted that the hazard function might not be monotonic in some cases, which requires testing of non-monotonic distributions for the parametric hazard models.

We examine AFT models and, we test both monotonic functions (i.e. Weibull and exponential distributions) and non-monotonic functions (i.e. log-logistic and lognormal distributions) to determine the best fit parametric hazard model.

As discussed in the literature review, in all of the formulations presented in this section, the terms duration and distance are interchangeable without losing generality of survival analysis. In the hazard formulation, the length of a duration spell for a subject is represented by a continuous random variable T with a cumulative density function (CDF), $F(t)$, and probability density function (PDF), $f(t)$. The probability of failing sometime before time t , $F(t)$ can be written as:

$$Pr(T \leq t) = F(t) \tag{1}$$

where t denotes the elapsed time since entry to the state at time zero.

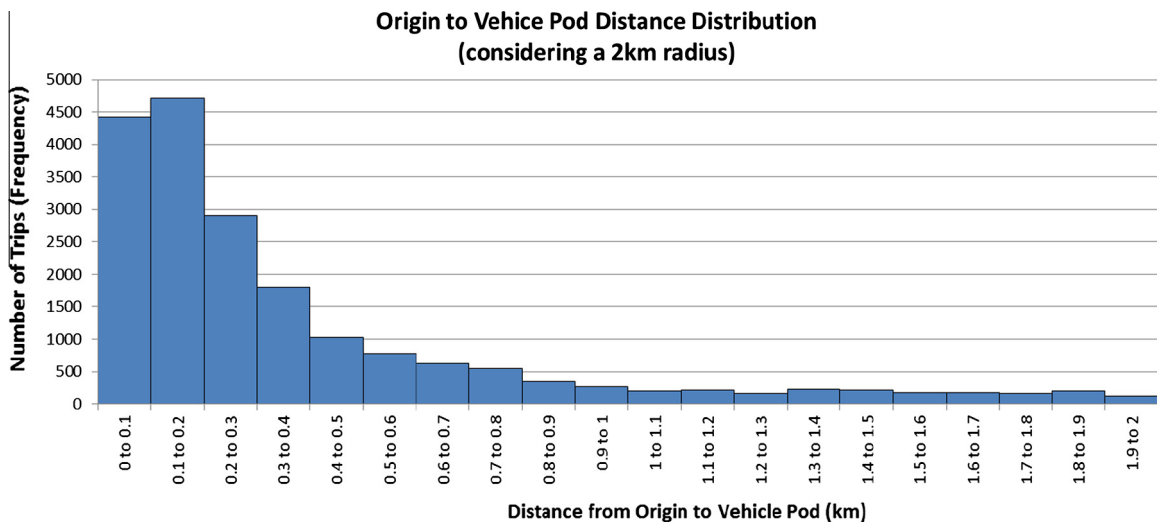


Fig. 1. Distribution of GoGet usage data considering a 2 km radius.

Then, the survival function can be written as:

$$\Pr(T > t) = 1 - F(t) = S(t) \quad (2)$$

As the slope of CDF is the PDF, it can be expressed as follows:

$$f(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T \leq t + \Delta t)}{\Delta t} = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} \quad (3)$$

where Δt is a very small time interval.

The hazard rate is defined as the probability of failure in the interval $(t, t + \Delta t)$ given that it has survived until time t . Let $\theta(t)$ denote the hazard rate, thus:

$$\theta(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} = \frac{\partial \{-\ln[S(t)]\}}{\partial t} \quad (4)$$

Using Eq. (4), the survival function can be defined as:

$$S(t) = \exp \left[- \int_0^t \theta(u) du \right] \quad (5)$$

As mentioned before, the AFT models are used, and they are formulated as:

$$\ln(t_j) = x_j \beta_x + z_j \quad (6)$$

where for individual j , x_j represents explanatory variables, β_x denotes the vector of coefficients, and z_j is the error with density $f(\cdot)$, which determines the regression model. By letting $f(\cdot)$ be the extreme-value density, the Weibull and exponential parametric hazard models are obtained. By ensuring $f(\cdot)$ follows a logistic distribution, the log-logistic hazard model is formulated. Similarly, by setting $f(\cdot)$ to a normal distribution, we obtain a lognormal regression model.

For the AFT model, $\exp(-x_j \beta_x)$ is defined as the acceleration parameter. If $\exp(-x_j \beta_x)$ equals to one, time passes at its normal rate indicating that failure will occur at the expected duration. If $\exp(-x_j \beta_x)$ is larger than 1, time is accelerated, that is, the failure is expected to occur sooner. If $\exp(-x_j \beta_x)$ is smaller than 1, then time is decelerated, which means the failure might occur later.

Using Eqs. (5) and (6), and the density functions, we rewrite the survival functions of these four distributions as follows:

$$\text{Exponential survival function : } S(t) = \exp[-\exp(-x_j \beta_x) t_j] \quad (7)$$

$$\text{Weibull survival function : } S(t) = \exp[-\exp(-p x_j \beta_x) t_j^p] \quad (8)$$

$$\text{Log-logistic survival function : } S(t) = (1 + [\exp(-x_j \beta_x) t_j]^{1/\gamma})^{-1} \quad (9)$$

$$\text{Lognormal survival function : } S(t) = 1 - \phi \left(\frac{\ln(t_j) - x_j \beta_x}{\sigma} \right) \quad (10)$$

where p is the scale parameter of the Weibull distribution, γ is the shape parameter of the log-logistic distribution, σ is the scale parameter of the lognormal distribution, x_j represents the vector of covariates, and β_x is the vector of coefficients.

In the context of this particular study the hazard based models are used to understand the formation of the vehicle choice set (Rashidi et al., 2012). Thus, t represents the distance between the user's origin and the available carshare vehicle. However, the critical acceptable walking distance for each type of vehicle is not known, only that it falls within some interval of distance between the selected vehicle and all the unselected vehicles of that type.

Fig. 2 helps explain the concept. As shown in Fig. 2, there are 7 types of GoGet vehicles available for users to select. Vehicles from different types have different attributes, while vehicles from the same type are exactly the same vehicles only with different distances from the origin of the user. As the carsharing network usually covers large urban areas, the vehicles from the same type are distributed sparsely with relatively long distances between each other. Since users will only consider the closest vehicle of each type of vehicle, there is only 1 vehicle from each type included in this data set. In this example, we assume that Vehicle 1 is selected by the user, but it does not mean that the distance to Vehicle 1 is the acceptable walking distance of Type 1 vehicles. Instead, the critical acceptable walking distance of the vehicle that is selected is somewhere farther than the distance of Vehicle 1, but closer than the second closest vehicle of that type (Vehicle 1'). Therefore, the probability of Type 1 vehicles being selected can be represented by the difference between the survival function of the selected car and the second closest car. For the type of vehicle that is selected in this trip, the probability being selected can be written as:

$$\Pr S(t \leq t^* < t') = S(t) - S(t') \quad (11)$$

where t' denotes the distance of the second closest vehicle.

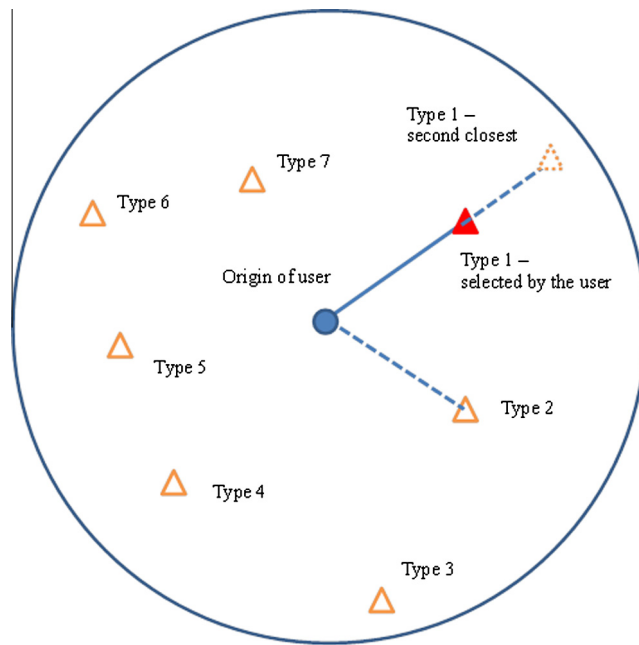


Fig. 2. Schematic explaining choice set formation of carsharing users.

As for the rest of the types of vehicles that are not selected, the acceptable walking distance is somewhere between the origin of the user and the distance of the vehicle. So for these types of vehicles, the probability being selected can be written as:

$$\PrNS(0 \leq t^* < t) = 1 - S(t) = F(t) \quad (12)$$

Eqs. (11) and (12) take into account the inclusion of the acceptable walking distance, and is used to formulate the maximum likelihood estimation model.

We develop four different hazard models in this research, therefore, it is necessary to compare the goodness of fit across these four models. The Bayesian Information Criterion (BIC) is employed to select the best-fit hazard model. It is the criterion for model selection among a finite set of parametric models. The model with lower BIC value is considered to have a better fit. The formulation of BIC is:

$$BIC = -2 \times \ln(\text{likelihood}) + \ln(N) \times k \quad (13)$$

where k denotes the number of the parameters estimated, and N is the number of observations.

5. Results and analysis

The four hazard based models were estimated using the statistical analysis software package SAS 9.4. Table 3 shows the results of parameter estimation. The signs of the coefficients, except $dl_country$ and $car_manufacturer_binary$, are consistent in all models.

In this case, the coefficient for $car_manufacturer_binary$ is statistically significant for the monotonic distributions (Exponential and Weibull), marginally significant for the Log-logistic distribution and insignificant for Lognormal distribution. The coefficient for $dl_country$ is statistically significant for the monotonic distributions (Exponential and Weibull) and statistically insignificant in the non-monotonic distributions (Log-logistic and Lognormal). This may suggest that the monotonic distributions might be anchoring their flexibility on these two variables and creating biases. Therefore, the non-monotonic distributions are more favorable functional forms.

As discussed in the Model Formulation and Methodology section, the BIC metric is employed to select the best-fit hazard model. With Eq. (13), we obtain Table 4 showing the results of BIC of all four models. The BIC value for the model with the Log-logistic distribution is 61380.67, which is the smallest among all the models. It can be concluded that the Log-logistic distribution provides the best hazard model among the four distributions considered for this study and as such this model is used for further analysis.

The hazard model with Log-logistic function is further examined. The estimated CDF is employed to simulate the distance between a GoGet user and his or her selected vehicle. Fig. 3 shows the simulated results for the cumulative survival probability with Log-logistic distribution. The general pattern is monotonically decreasing, which is consistent with observations.

Table 3
Parameter estimation results for four models.

	Parameter	Exponential		Weibull		Log-logistic		Lognormal	
		Estimate	t Value	Estimate	t Value	Estimate	t Value	Estimate	t Value
User	User_age	0.478331	7.278972	0.479827	7.290833	0.525723	9.315292	0.560786	9.661856
	User_car_ownership_binary	-4.401545	-2.322136	-4.466535	-2.360376	-10.5214	-6.326725	-7.38349	-4.35386
	User_how_often_use_car_binary	0.403781	0.26871	0.273092	0.181628	2.233314	1.593125	0.953487	0.674687
	User_main_way_to_work_binary	3.706292	2.575694	3.624778	2.517515	5.957318	4.435694	5.851677	4.311006
	User_landuse_binary	6.301275	4.080201	6.365917	4.125418	7.694193	5.397969	6.966072	4.876655
	User_live_near_dedicated_parking	9.767516	6.272694	9.911045	6.374452	11.9866	8.333365	11.37041	7.880726
	DI_country	-2.733833	-1.529486	-2.716028	-1.520406	0.495685	0.28573	1.885583	1.067935
	Plan_binary	-4.750974	-3.049809	-4.948086	-3.178989	-6.926405	-4.78561	-6.380722	-4.382184
Vehicle	Booking_method_binary	7.110488	3.336593	7.008435	3.289569	4.290644	2.135171	5.771724	2.919326
	Car_manufacturer_binary	13.03322	5.850823	11.68059	5.168007	-3.954376	-1.457152	0.634384	0.256958
	Car_body_type_binary	-18.556	-6.539107	-21.13242	-7.563846	-65.90859	-20.13298	-48.54587	-16.3952
	Car_age	-5.111518	-4.937334	-5.42193	-5.286265	-6.401082	-7.049798	-5.816886	-6.375166
Trip	Pet_friendly	-63.86401	-17.49671	-66.31779	-17.973218	-89.33228	-19.186386	-80.91573	-20.335366
	Trip_travel_time	13.72318	7.150655	13.73324	7.030809	4.970142	1.464533	5.147012	2.523356
	Usage	1.224163	20.79797	1.310191	20.733937	1.052602	21.33739	1.251509	26.68257
	_cons	-1.771756	-35.98064	-1.715665	-35.772448	-2.118267	-48.110867	-2.216295	-49.637059
	Weibull_p	-	-	0.956884	126.36897	-	-	-	-
	Loglogistic_gamma	-	-	-	-	0.50636	138.5621	-	-
	Lognormal_sigma	-	-	-	-	-	-	0.937571	137.24704

Table 4

Calculation results of BIC of four models.

	Exponential	Weibull	Log-logistic	Lognormal
Log likelihood value	−31367.11	−31344.32	−30596.28	−30695.03
Number of observations	63,933	63,933	63,933	63,933
Number of parameters	16	17	17	17
BIC	62911.27	62876.76	61380.67	61578.18

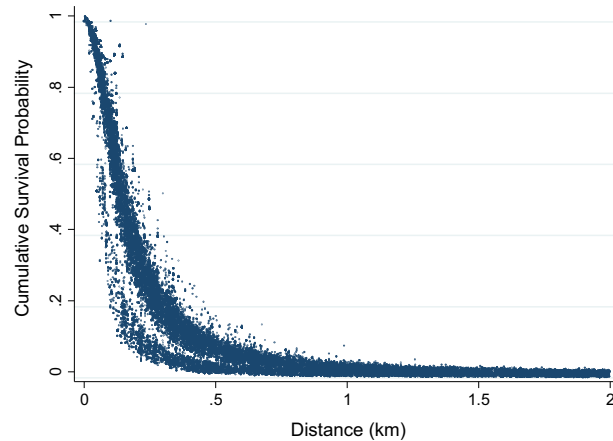
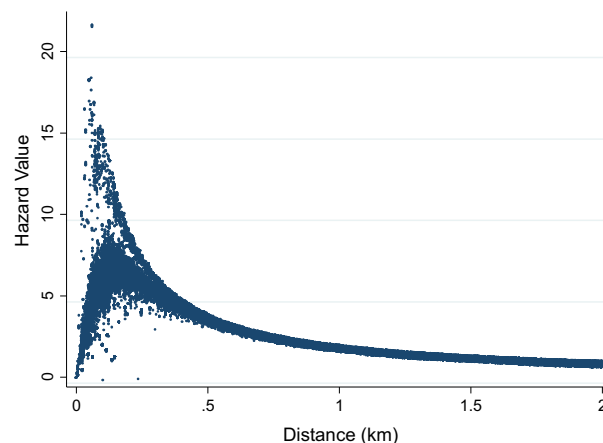
**Fig. 3.** Cumulative survival probability pattern for Log-logistic model.

Table 3 presents the parameter estimation results of Log-logistic distribution. As shown in the table, the γ parameter of Log-logistic distribution is smaller than 1, meaning that the shape of Log-logistic hazard model is not monotonic. The hazard rate will first increase to a certain value and then decrease as the distance between the user and the vehicle increases.

Fig. 4 plots the pattern of the hazard value against the vehicle distance, which confirms the non-monotonic interpretation of the γ parameter for the Log-logistic distribution. In Fig. 4, the hazard value first increases as the distance increases. When the distance is approximately 0.2 km, the hazard value starts to fall. This can be explained that when the walking distance is within 0.2 km, users are not affected by the distance to the vehicle. Another reason might be that only 20% of the vehicles are within the 0.2 km radius, so users do not have enough choices regarding the vehicles within 0.2 km. When the distance is larger than 0.2 km, the impact of the distance on users' vehicle selection behavior becomes more significant. Users prefer to select vehicles that are nearer to their origin locations, which satisfies the initial assumption and common sense of car-sharing vehicle selection.

Before discussing the results of the parameter estimation, it should be noted that in the AFT models, the effect of covariates is facilitated by incorporating a negative sign for the parameters within the formulation. In other words, if the coefficient (β_x) of the covariate is estimated to have a negative value, the expected time to failure decreases and the probability of failure

**Fig. 4.** Hazard pattern for Log-logistic model.

increases. In the context of the vehicle selection of this paper, this means that an individual with a larger value of the covariate tends to choose vehicles with shorter distances between the origin and vehicle pod. Conversely, if β_x of a covariate is positive, an increase in the value of the covariate increases the expected time to failure. This means that an individual with a higher value of this type of covariate tends to accept a greater distance between the origin and vehicle pod.

The parameter estimates for the Log-logistic distribution shows that most of the parameters listed are statistically significant at a 5% confidence level except the binary variable *dl_country*. Among the parameters, the coefficients of all the vehicle related parameters are negative. The binary car manufacturer variable has a negative coefficient which indicates that people who selected a non-luxury (as defined in Section 3) carsharing vehicle (i.e. not an Alfa Romeo) have the tendency to commute longer to the vehicle pod. This finding can be explained by the fact that the rate of these luxury vehicles is higher than other normal vehicles. Since carsharing is reported to be more popular among individuals with lower incomes who might value lower transportation costs more than the extra aesthetic and comfort based utility of the vehicles (Costain et al., 2012). Thus, users are more willing to select vehicles with lower hourly rates at the expense of walking longer distances. Furthermore, the car body type variable also has a negative coefficient estimate suggesting that users' selecting hatchback vehicles are more likely to travel longer distances to the vehicle pods, while users choosing multi-purpose vehicles (MPVs) or electric vehicles have higher probability to travel shorter distances to find a vehicle. This can be explained by the general household characteristics of carshare users. Celsor and Millard-Ball (2007) indicated that the more common users of carsharing facilities are people who are from single occupant households. In general, this category of user will not have the requirement to use a large vehicle or an MPV as there normally isn't the need to transport more than a few people. In addition, the short-term nature of carsharing use means that the trip purpose for a lot of journeys are short term and do not require the use of large vehicles which are more common for holiday and long term car rental (Cervero et al., 2007). So even if the hatchback is relatively far away from the origin, the user will be inclined to hire it over a MPV or a larger vehicle. With respect to the electric vehicles, since electric vehicles are not as common as conventional petroleum vehicles, users might prefer petroleum vehicles regardless of the distance to the vehicle pod due to familiarity. It is interesting to note that the age of the car also has a negative coefficient, meaning that as the age of the car increases users' willingness to travel farther to the vehicle must reduce significantly. This is an intuitive result as the common perception of users is that newer vehicles are more reliable and as such there is value in walking a greater distance to obtain a better vehicle.

It is clear that car ownership also has a negative coefficient, suggesting that users who own a car are more willing to select vehicles that are closer to them. In other words, people not owning a car but intending to use a carsharing service have higher probability to travel a greater distance to the vehicle pod. People who own a car have the choice to not use a carshare vehicle if the distance to the vehicle pod is too great. But for those people who do not own a car, they might not have any alternative except using carshare vehicles if they absolutely need to make use of a private vehicle. This result is consistent with the result of the binary *user_main_way_to_work* variable. The coefficient of this variable is positive meaning that users who use public transport to travel to work originate farther from the vehicle pod. This category of user may not own a private vehicle, but more importantly do not have access to a vehicle during work hours and as a result if they need to complete a trip requiring a private vehicle during that time they may be forced to travel a greater distance to the vehicle pod. In addition, the *plan_binary* variable has a negative coefficient suggesting that more frequent users of carsharing services tend to select vehicles within shorter distances from their origin. This may be attributed to the scenario where people who live near or have easy access to carshare vehicles are more likely to be involved with a frequent use carshare plan, due to the convenience of the vehicle pod locality relative to their residence.

The variable *pet_friendly* was found to have a negative coefficient, suggesting that pet friendliness is not an extra benefit for most carshare users. This is intuitive in that pet owners who are regularly travelling with their pet generally own pet friendly car. The negative correlation between *pet* and *car_body_type* also helps explain the result: pet-friendly vehicles are more likely to be hatchbacks, and the majority vehicles provided by GoGet are hatchbacks.

Observing the positive coefficients, the covariate *usage* has a positive sign indicating that users prefer to walk further for cars that they have selected and used multiple times. This is also a logical outcome in that users value the reliability and familiarity of the vehicle more than the distance to the vehicle. Considering a similar rationalization, users that have greater carsharing trip lengths tend to select vehicles located further away from their origin. Again, this could be attributed to the fact that when the user is planning a longer trip, they are more likely to choose a car that is more suitable to the purpose of the trip and familiar to the user regardless of the distance to the car. Increased usage of cars (*user_how_often_use_the_car_binary*) by a user suggests an increase in the distance between the origin and the vehicle pod when selecting a carsharing vehicle. This is a contrasting result to what was observed with the car ownership variable even though this variable indication is attributed to the ownership of a private vehicle. There are a few explanations for this result: initially owners of private vehicles are less likely to use carshare facilities, as a result there is no utility for people to be originated within the vicinity of the carshare service, however when they do need to use the service they will need to travel further to gain access to the facility. Furthermore, within Australia, carsharing vehicles have priority parking spaces throughout built up CBD areas where parking is a premium and accordingly users' may find it more convenient to use the carshare facility ahead of using their own private vehicle.

The users' age also has a positive coefficient suggesting the older a user, the farther his or her origin is to the vehicle pod. Elderly users may not own a private vehicle and also may have more leisure time, as a result distance to the vehicle pod is either inevitable or does not impact their utility as much as younger users. Variables linked to characteristics of the users' origin prior to using the carshare facility present positive coefficients (*user_landuse_binay* and *user_live_near_dedicated_parking*). This suggests that people originating from residential zones, living in a suburban environment, tend to travel further to

gain access to a carshare vehicle as these trips may involve a greater level of planning relative to those happening situated in commercial and industrial zones. It can also be explained, that users from commercial and industrial zones, who live in an urban environment, have a greater mode choice (access to taxis and public transport) reducing their tendency to walk large distances to use carsharing facilities. Further, residing near a dedicated GoGet parking area increases the incentive to access carsharing services and results in users' willingness to travel greater distances to make use of the facilities.

Interestingly, the variable *booking_method_binary* was found to have a positive coefficient and is statistically significant. The variable takes a value of one if the booking was done using a mobile application and zero if other methods were used. The statistically significant positive coefficient suggests that people are willing to travel further to access the carshare car when using the mobile application, which reflects their flexibility to access the vehicle based on real time information about other transportation options.

6. Conclusion and future directions

This study presented a behavioral model to gain a greater understanding of users' selecting vehicles within a carsharing program. The study attempted to answer two questions: "How far is an acceptable walking distance when users make decision on using carshare vehicles?" and "What factors influence users' selection of vehicles and are there any patterns or trends associated within these factors?" An answer to these two questions enable the researcher to model the choice set formation behavior as a probabilistic process which is a function of distance and the identified covariates.

As the vehicle selection process is complicated, a choice set formation methodology using a spatial HBM was developed using a rich data set from the Australian carsharing company GoGet. The SHBM considered "distance to the carsharing vehicle" as a non-negative random variable analogous to the duration of conventional HBMs. The results from the modelling contain a number of negatively and positively correlated covariates which can provide trends and patterns that could potentially be used to guide policy of carsharing programs. Positive coefficient estimates implied that as the value of the independent variable increases users tend to travel a further distance to select a carshare vehicle. Negative coefficient estimate, on the other hand, indicated the opposite where an increase in the variable means that users favor to travel a shorter distance to select the vehicle.

The user age, frequency of usage of cars, users' main way to work, booking method and users' land use type had positive coefficients. These results indicate that elderly users, users taking public transport to work, users with frequent usage of cars, users used mobile phones to book a trip, and users from residential areas tend to originate farther to the vehicle pod. The number of times a user selects a specific GoGet vehicle and trip travel time also had positive coefficients. This demonstrates that user's value familiarity with the vehicle and age of the vehicle over the walking distance to the vehicle from the origin.

On the other hand, users' car ownership and plan type variables had negative coefficient estimates. This demonstrates that the vehicles located within a shorter distance to the origin have a higher probability of being selected by the users who own a car and the users who join a frequent use carshare plan. The car manufacturer, car body type, car age and whether the car is pet friendly also had negative coefficient estimates. This may suggest that the luxury vehicles, vehicles with specific body type, old cars, and vehicles that allow for carrying pets along do not have enough incentive to users compared to those newer vehicles and vehicles with lower hourly rates and smaller size. These "normal vehicles" are more likely to be selected even if they are further away from the users. Based on these trends, carshare organizations can optimize their vehicle pod locations to center on catchments containing these user classes to maximize usage of the system as well as enhance the overall popularity of the scheme.

The increase in use of carshare systems has created questions for transportation agencies to provide and manage existing parking locations for carshare systems to increase their use, and influence car ownership. The model presented in this paper will help carshare operators understand how users formulate the vehicle selection choice set, and predict the probability of a vehicle being selected together with the advanced discrete choice model being formulated in the next step. The two models can further be integrated with an optimization model aiming to optimally select the locations and types of vehicles in the carsharing programs given a set of candidate vehicles. The SHBM together with the secondary discrete choice model can provide the probability of a vehicle selected given the location and the characteristics of the vehicle. The objective of the optimization model can be maximizing the carshare ridership by maximizing the sum of the probability of vehicles being selected by users given a budget constraint. The integrated model can determine the optimal locations of carshare vehicles and the types of vehicles that can enhance the overall popularity of the carsharing scheme.

Further extensions of the current study include investigating the importance of key variables other than the "distance to the carshare vehicle" that impacts the vehicle selection process within a carshare scheme, such as trip purpose and trip destination. In addition, the impact of the types of vehicles (hatchback/MPV/electric vehicle) and the manufacturers of the vehicles could also be further refined as individual covariates to see if an impact is observed. Moreover, the application of the SHBM model can be extended to hilly areas with different pedestrian walking conditions compared to Sydney by converting the distance used in this model to walking time.

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