On-Street Parking Choice Models Based on a Stated Preference Game Simulation Survey

by

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A thesis submitted in conformity with the requirements for the degree of Master of Applied Science

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Stated Preference Simulation Survey Design and Discrete Choice Modelling of On-street Parking

Obtaining a better understanding of on-street parking behaviour in city centres by estimating different model structures using data collected from a parking simulation game SP survey

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Abstract
This study develops a stated preference survey, named iCity Park, as a parking simulation game to collect drivers’ on-street parking choices when legal and illegal parking spots are available, and parking enforcement is present. The gamification incentive and simulated hypothetical scenarios in the survey are proven to be effective for high-quality data. iCity Park also simulates parking activities with and without ITS assistance. This study develops three types of logit models for the two assistance levels. The estimated mixed logit models have the best goodness of fit and demonstrate the significance of respondents’ parking preference heterogeneity. Then models for the two assistance levels are compared, and the influential power of the explanatory variables are analyzed. This thesis contributes to innovative data collection methods and provides a better understanding of parking choice process and parking behavioural changes with the assistance of parking information systems.
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<tbody>
<tr>
<td>ASC</td>
<td>= Alternative specific constant</td>
</tr>
<tr>
<td>ASV</td>
<td>= Alternative specific variable</td>
</tr>
<tr>
<td>ATIS</td>
<td>= Advanced Traveller Information System</td>
</tr>
<tr>
<td>GPS</td>
<td>= Global Positioning System</td>
</tr>
<tr>
<td>IGOR</td>
<td>= Interactive Guidance on Route</td>
</tr>
<tr>
<td>IIA</td>
<td>= Independent of Irrelevant Alternatives</td>
</tr>
<tr>
<td>IID</td>
<td>= Independent and Identically Distributed</td>
</tr>
<tr>
<td>ITS</td>
<td>= Intelligent Transportation System</td>
</tr>
<tr>
<td>MNL</td>
<td>= Multinomial Logit</td>
</tr>
<tr>
<td>MXL</td>
<td>= Mixed Logit</td>
</tr>
<tr>
<td>NL</td>
<td>= Nested Logit</td>
</tr>
<tr>
<td>PDF</td>
<td>= Probability Density Function</td>
</tr>
<tr>
<td>PGI</td>
<td>= Parking Guidance and Information</td>
</tr>
<tr>
<td>POI</td>
<td>= Point of Interest</td>
</tr>
<tr>
<td>RP</td>
<td>= Revealed Preference</td>
</tr>
<tr>
<td>RUM</td>
<td>= Random Utility Maximization</td>
</tr>
<tr>
<td>RUT</td>
<td>= Random Utility Theory</td>
</tr>
<tr>
<td>SP</td>
<td>= Stated Preference</td>
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Chapter 1 Introduction

Parking policies have high impacts on drivers’ parking choice behaviour, especially in congested urban centres where the parking capacity is limited. The parking fare, parking space distributions, illegal parking enforcement level, and illegal parking fine, which are all set by local parking policies, affect travellers’ choices of parking location, parking type, dwell time, and even influence their travel mode choice. People’s travelling and parking choices are essential to the transportation system. For example, cruising for parking, which is a typical behaviour due to underpriced and overcrowded curbside (on-street) parking, generates additional and significant traffic delays to the already congested traffic, especially during peak hours in urban centres (Arnott and Inci, 2006). The pricing policies of on- and off-street parking are major reasons for this phenomenon as parking selection and cruising for parking are essentially an economic decision. Other factors are involved besides the parking fare, such as the capacity of different types of parking facility and distribution of parking spaces. Parking choices between legal and illegal parking are affected by parking policies as well, such as parking fare, illegal parking enforcement and fine. Illegal parking has adverse impacts to local transportation system such as reduced traffic flow (Ramadan and Roorda, 2016), safety issues (Conway et al., 2013) and loss of revenue from legal parking. Parking policies also affect travellers’ mode choice and travel demand. People may switch to public transit from private vehicles as a response to parking policy changes (Simićević et al., 2013) that make parking spaces difficult or time-consuming to find, or relatively expensive. Therefore, it is essential for policymakers to understand driver’s parking behaviour in response to changes in parking policies and their potential impacts and associated consequences on the social welfare and transportation systems.

During the past few years, intelligent transportation systems (ITS) have had an enormous impact on the transportation system with significant improvements through the use of advanced technologies. ITS applications for parking have recently been developed and made available for the public. Parking guidance and information (PGI) system is the most popular one. It provides detailed parking information to drivers and assists them with parking selections. It is believed that PGI systems will change the way people make parking decisions and potentially will bring numerous benefits (Axhausen et al., 1994; May and
Turvey, 1984; Arnott and Inci, 2006). The impacts of changed parking choice behaviour due to PGI systems and other ITS applications on the transportation network are significant, and they have influences on parking policies. Thus, it is necessary to evaluate the influence of new parking technologies on drivers’ parking strategies in the context of parking policy.

On-street parking choice behaviour of drivers is more complicated than off-street parking because of higher vacant spot dispersion, more parking space choices and the presence of illegal parking. Consequently, it is difficult to obtain data and analyze on-street parking choice behaviour. Furthermore, on-street parking faces more challenges for making parking policies and incorporating ITS applications. More factors are considered and designed for on-street parking than off-street parking. They are mainly related to illegal parking and parking space distribution. For parking information applications, on-street parking requires installation of embedded sensors for all spots or on-street cameras to collect vacancy data; while off-street parking only needs a vehicle counter to perform the same function for each garage or parking lot. Therefore, the interaction between people’s parking choices for on-street parking and parking policies/ITS applications should be carefully studied for effective policymaking and efficient high-tech system design.

1.1 Objectives

The objectives of the thesis are as follows:

- To collect data about on-street parking choices when legal and illegal parking spots are available, and parking enforcement is present, considering many influential factors, such as dwell time, parking search time, parking rates, occupancy rate, illegal parking citation probability and fines.
- To design a stated preference (SP) survey as a gamified travel simulator for data collection to effectively present hypothetical scenarios and expose respondents to a wide range of attributes.
- To understand the effects of various parking attributes on driver’s parking choice processes, through estimating discrete choice models with different structures that predict an individual’s parking choices under different scenarios of influential factors.
To evaluate the functions and influences of parking ITS applications (PGI and parking reservation systems) on an individual’s parking choice behaviours.

1.2 Methodology

First, a stated preference survey is developed as a simulation game to collect parking choice data and respondents’ characteristics. The survey, named iCity Park, begins with a parking simulation game that requires respondents to perform parking tasks in a five-by-five grid network under different hypothetical scenarios, which are set by using orthogonal fractional factorial design. The parking game section includes two different parking assistance levels, and they represent conventional parking tasks and assisted parking tasks with parking information systems. The second part of iCity Park consists of a series of socioeconomic questions, designed to investigate their correlations with respondents’ parking preferences.

After running the survey, the collected data is organized and processed to prepare the necessary variables for model estimation and formulation. The data processing includes computing parking access time, defining choice sets, computing alternative attributes that involve averaging attribute values within each alternative, and classifying parking alternatives. The processed data is used to develop three types of regression models (MNL, NL, and MXL), which identify the significant factors that affect parking choice behaviour and estimate the coefficients of the factors to indicate each factor’s influential power for different types of parking scenarios. Also, respondents’ parking choice processes can be learnt through the three different model structures. The obtained data and developed models for different levels of the game are then compared to evaluate the influences of parking ITS applications, such as PGI and parking reservation systems, on people’s parking behaviour.

1.3 Thesis Outline

This thesis consists of seven chapters. Chapter 1 introduces the underlying motivations for the study, objectives and general methodology. Chapter 2 reviews existing literature which provide background information of parking choice studies as well as references for the design of the data collection method used in this thesis. Chapter 3 explains the detailed design of the simulation game survey, iCity Park, and proposed discrete choice model
structures. Chapter 4 presents the processed parking choice data from the survey with analysis of the respondent’s demographic attributes and parking alternative frequency analysis. Chapter 5 provides the detailed modelling process and final models, and the models are compared and analyzed. Chapter 6 concludes by discussing the effectiveness of the innovative data collection method and summarizes the key findings and recommendations for future work.
Chapter 2 Literature Review

2.1 Introduction

Existing research studies about parking choice analysis are reviewed, and they can be classified into two main categories, which are studies on parking choice determinants and studies on the methodological issues related to the collection and modelling of parking choice data. There are two primary data collection methods for parking choice behaviour, namely revealed and stated preference approaches. Despite each approaches’ strengths, they have weaknesses that could limit their usefulness and model development. Parking simulation overcomes some of the shortcomings of these two methods, and gamification could potentially provide effective incentives to respondents. This section discusses the above topics in detail and reviews existing research studies that focus on parking choices and related intelligent parking systems.

2.2 Stated Preference and Revealed Preference Survey

Drivers choose on-street parking spots from a set of vacant ones around their destinations. Typically, a driver chooses the most convenient parking spot based on factors such as parking cost, destination location, etc. Discrete choice modelling is a technique that can identify and evaluate influential factors in parking choices. The development of discrete choice models requires sufficient data inputs, which come from data collection. Data collection is commonly conducted using surveys, which can be classified as revealed preference (RP) surveys or stated preference (SP) surveys. Revealed preference refers to information collected about driver parking spot choices made in real life, while stated preference surveys ask respondents to choose a parking spot from a set of alternatives based on their attribute values in different hypothetical scenarios. There are numerous studies that develop and conduct RP and SP surveys to collect parking choice data (Ergun, 1971; Austin, 1973; Kelly and Clinck, 2009; Axhausen and Polak, 1991; Habib et al., 2013). However, both methods have drawbacks which limit their use.

The most challenging issue related to RP surveys is the complexity of defining the choice set and obtaining attribute values of non-chosen alternatives. The set of all available parking
spots along the routes on which the drivers are cruising for parking is the “choice set”. Capturing the choice set is challenging since it requires information on the availability of each of the non-chosen parking spots, and those alternatives’ attributes may be unobserved by drivers. Also, it is resource-intensive to obtain the choice set’s attribute values if there are too many alternatives, each with different attributes. Consequently, obtaining each driver’s parking choice set and related attribute values usually requires the assistance of technology. Axhausen and Polak (1991) discuss the complexity of collecting parking choice data through RP surveys and emphasize that even after paying a considerable amount of effort, it is impossible to define the choice set of parking activities with available technology. Even today, conducting RP surveys for parking with a defined choice set is a daunting task, as it would require GPS data from participants who perform parking tasks in a given study area and occupancy data from street cameras or sensors embedded in the on-street parking spots. These cameras and sensors are only implemented in limited regions of few cities in the world, such as San Francisco and Washington D.C. Nonetheless, many studies approach RP data collection issues using different methods. Ergun (1971) developed a parking choice logit model and defined the choice set by classifying the parking spots according to their distance from the destination. Austin (1973) and Gillen (1978) tried the same approach, which grouped available parking spots according to their relative locations or the walking time to destinations. In contrast to those studies that distinguish parking spots solely by locations, Van der Goot’s (1982) study in Haarlem also considered parking types in the choice set classification along with parking location. Van der Goot categorized parking spots in the centre of Haarlem into 22 groups based on their types and locations. The developed utility functions provided more accurate parking choice predictions, and the results indicated that the grouping consideration on parking types is significant. Kelly and Clinch (2009) conducted a RP survey to estimate on-street parking price elasticity and tried to solve the choice set problem by limiting their test area to a small central area with on-street parking in Dublin. However, the grouping approaches that consider location only or location and type for the choice set have several drawbacks. First, it would be challenging to understand the power of influential factors on parking choices because some of them have a strong inverse relationship, such as parking price and walking distance from the parking spot to the final destination. Second, the defined choice set which is grouped according to location and type
makes the estimated model specific to a particular parking distribution; thus this approach restricts policy testability and transferability (Axhausen and Polak, 1991).

SP surveys address some shortcomings of RP surveys since SP surveys define the choice set for respondents and vary the attribute levels of influential factors under hypothetical scenarios. The scenarios in SP surveys provide practical and hypothetical alternatives and an extended range of attribute levels for respondents. Therefore, the estimated models are able to evaluate each attribute’s influence. They are capable of testing policies that are not currently implemented in the real world. SP survey methods are used in many studies. For example, Axhausen and Polak (1991) used disaggregate data collected from a SP survey to model driver’s sensitivity of parking choices to changes in parking attributes. Habib et al. (2013) conducted a SP survey to investigate the influences of parking charges on parking at transit stations and mode choice behaviour in Vancouver. In this study, attributes of parking cost and occupancy level are varied for different scenarios. Other studies that used SP surveys as the data collection method were concluded in Karlsruhe (Axhausen 1989) and Kingston upon the Thames (Bradley and Layzell 1986).

The choice set for SP surveys could be too large as a result of abundant attributes and alternatives. For instance, a full-factorial design with three alternatives, three attributes, and three attribute levels would result in 19,683 choice sets or scenarios, which would make the survey time-consuming. In this case, the alternatives refer to respondents’ parking spot choices, the attributes refer to the characteristics of each parking spot, such as parking rate and availability, and attribute levels refer to the degrees of each spot’s characteristic, such as different parking rates. Then a specific combination of attribute levels generates one scenario. Although fractional factorial designs, which select a subset of the full factorial design, are usually used, they can result in biased model estimation (Caussade et al., 2005; Hensher, 2006). For example, Axhausen and Polak (1991) initially designed a SP survey with five alternatives and 20 factors. They realized that the choice set would be too large, which made the survey too complicated and inefficient. Consequently, the alternatives were limited from 5 to 3 and some attributes only had/were assigned one level by making some assumptions of the parking situation and behaviour, to reduce variables and simplify the choice set. In order to reduce the size of choice set, Golias et al. (2002) also limited their
parameters to parking spot search time, walking time between the parking spot and the
destination, and the parking cost. They also reduced the number of attribute levels by making
assumptions, such as zero search time for off-street parking. With the limitations discussed
above which are inherent in RP and SP surveys, there is a need for novel data collection
methods that can capture the choice set without limiting the attribute-factor space (number of
attributes and attribute levels).

2.3 Parking Simulation Data Collection

Simulators are artificial duplications of a system or equipment, in which human interaction
and input lead to changes in the simulated system as it does in reality. Simulators were first
widely used for training purposes, such as flight simulators (Jones et al., 1985), and they
have been used for design and evaluation of standards and systems by learning the outcomes
of simulated scenarios.

Travel simulators are commonly used to collect travel behaviour data in transportation
networks. Travel simulators overcome some deficiencies of RP and SP surveys. First,
simulation platforms are able to present the hypothetical scenarios of the SP surveys in a
controlled environment, and the simulated environment implicitly exposes respondents to a
wide range of attributes and factors whereas SP surveys use only a subset of the attribute-
factor space. Second, travel simulators are able to capture the significance of specific factors
as compared to RP surveys. For example, repeatedly chosen alternatives in simulators are
cased by respondents’ perception of the significance of specific attributes and learning
through experiences, whereas they are the results of uncontrolled factors that catch
respondents’ attention in RP surveys. Lastly, respondents’ preferences for new alternatives or
features can be tested using simulations, so data collection by simulators has the capability of
exploring the impact of technologies that are still under development such as parking
guidance system (Koutsopoulos et al., 1995).

The feasibility of travel simulation data collection has been demonstrated in many studies.
Bonsall and Perry (1991) were the first to design an interactive route-based simulator, IGOR,
to collect data for identifying factors that influence travellers’ response to route choice
guidance. The simulator successfully collected data about respondents’ responses to routing
advice in a hypothetical fixed network, and their conclusions contribute to advanced traveller information system (ATIS) design. Bonsall et al. (1997) used a route choice simulator, called VLADIMIR to collect data for estimating route choice under different types of ATIS, and Chen and Mahmassani (1993) developed a similar simulator which collected all types of user choices, such as route departure choice, en-route diversion decisions and route choices. The technology related to parking, such as parking information or guidance systems, is still under development, and thus few research studies have been conducted that collect driver parking choice data by travel simulators.

PARKIT is a travel simulator that collects data for the purpose of evaluating the impact of technologies, such as parking guidance and information (PGI) system on parking behaviour (Bonsall and Palmer, 2004). PARKIT provides a detailed environment and mimics real travel experience by including features such as drive control, parking space searching, queuing, journey context and audio-visual stimuli. The simulation session asks respondents to complete five journeys and answer questions at the end. Each journey involves a parking task with the assistance of PGI systems and some provided information about certain parking spaces, such as cost and final walking distance. The simulator maintains a log of all choices made by respondents, which is impossible to obtain from conventional data collection methods. The richness of the database and the high level of experimental control provide the potential for behaviour analysis. However, PARKIT is designed for off-street parking only, so there is still a need for a travel simulator that collects data that captures the parking choice behaviour for on-street parking. The level of complexity for on-street parking is higher due to higher dispersion of vacant on-street parking spots, more complex attribute variations and the possibility of illegal parking.

2.4 Gamification Concepts as Incentives

Motivating respondents to participate in and complete a survey is difficult, and thus an incentive is required to accomplish a high participation and completion rate. Incentives can be classified into three categories (Wang et al., 2016): extrinsic (economic) incentives, intrinsic (entertainment or game-based) incentives, and internalized extrinsic (reputation based) or social incentives. Among the three types of incentives, Wang et al. (2016)
considered gamification as the most effective in engaging people to conscientiously perform tasks and provide high-quality data. The other two have some limitations. Consequently, they collected data and feedback through gamified surveys for mobile crowdsourced sensing (MCS). Although the other two types of incentives may result in higher participation rates, the quality of collected data with extrinsic incentives is lower compared to intrinsic incentives. Social incentives involve challenges of identity management issues (Wang et al., 2016). Arakawa and Matsuda (2016) also introduced gamification mechanisms such as awarding of levels, badges and ranking, as a substitute for monetary incentives, into their participatory urban sensing, which crowdsources data and information from the public. They found that the participation rate increased 20 percent after they gamified the process. Kashian et al. (2014) designed a mobile application, RoadPlex, to collect attribute information for POIs (Points of Interest) such as positional data, business hours, and pictures of stores on maps. However, the process was boring because the contributions of detailed information were not as striking as adding new roads or reporting new stores, and thus the participants experienced low satisfaction levels. Therefore, the designed application involved gamification concepts, such as points/coin rewards and rankings, to motivate the public to participate and provide accurate attribute information. The methodology of using gamification concepts as incentives was confirmed to be effective since the number of participants increased after releasing the game. Kazhamiakin et al. (2015) explored the potential of gamification incentives for voluntary behavioural change. They developed an application that provided mobility recommendations to users, and users could obtain points and gather badges if they took sustainable transportation, such as biking, walking, and park & ride. The case study was conducted in the City of Rovereto (Italy), a city with high traffic pressure. The results indicated a high participation rate with the introduction of gamification to the application software, which resulted in a higher percentage of sustainable trips in Rovereto. Although gamification incentive is proven to be an effective motivation in data collection processes, there have been few studies, such as PARKIT application (Bonsall and Palmer, 2004), that conduct SP surveys that involve gamification concepts to collect driver’s parking choice behaviour.
2.5 Parking Technology Development and Current Parking Application Review

Technology advancements in the past few decades have led to the development of intelligent transportation systems (ITS), which involves technologies such as wireless communications, computational technologies, sensing technologies, etc. ITS applications for parking systems for the public have started to develop in recent years with the popularization of personal communication devices, such as smartphones and tablets. One of them is parking guidance and information (PGI) system, which integrates traffic monitoring, communication and information processing to provide real-time information on parking. PGI systems are developed and implemented in major cities around the world and are available to the public through personal communication devices. For example, an application on smartphones called “VoicePark” provides real-time information on parking to the application users and has turn-by-turn guidance to selected parking spots. The parking information covers on-street (curbside) parking in 7 major U.S. cities and off-street (garage or lot) parking in over 40 cities in the U.S. and Canada. The information includes the parking type, availability, rates for different hours, accepted payment types, driving time to the parking spaces, walking time from the parking to user’s destinations, contact information for off-street parking, etc. VoicePark also has reservation functions, and users can reserve their selected parking for both on- and off-street parking spots for certain time slots before starting their trips. There are many other smartphone parking applications that are similar to VoicePark, such as BestParking, Honk, SpotHero, and Parking Panda. They are mainly used for off-street parking only since on-street parking information requires embedded sensors, which are only available in a few cities, such as San Francisco. PGI systems have the potential to save travellers’ parking search time. Some surveys conducted in British cities indicate that parking space searching time accounts up to 25% of the total travel time of journeys to central urban areas (Polak and Vythoulkas, 1993) and the proportion could go up to 50% during peak hours (Axhausen et al., 1994; May and Turvey, 1984; Arnott and Inci, 2006). Therefore, PGI systems with full compliance of users could lead to a reduction in an average journey time of up to 50% and substantially reduce traffic congestion in central regions. Apparently, PGI systems are most effective for drivers who are unfamiliar with the local parking sites around
their trip destinations and so have no strong parking preferences. The system can provide those drivers with the locations of and guidance to available parking spaces. For drivers with local parking knowledge, they would make trade-offs in parking choices with the detailed parking information provided by the systems, such as search time, walking time, price, etc. Therefore, PGI and parking reservation systems, as new methods for making parking choices, could potentially change people’s parking behaviour. Thus, it is important to obtain a profound understanding of people’s parking choice behaviour with and without the parking systems, along with the systems’ influences on other aspects of the transportation system, such as traffic conditions, emissions and traffic safety.

2.6 Parking Choices and Their Determinants

Parking policies and their resulting parking patterns have great impacts on the transportation system, and researchers have developed algorithms and simulation models for their evaluation. To name a few, Ramadan and Roorda (2017) presented a traffic microsimulation model to quantify the impact of illegal on-street parking in the City of Toronto. The model results showed that, on average, illegal on-street parking activities increase traffic delay by 50% and reduce traffic flow by 7% as compared to simulations without illegal parking. Nourinejad and Roorda (2017) investigated the impacts of parking pricing on travel demand and analytically proved that it could reduce or induce demand depending on the elasticity of parking dwell time for a small network. They further validated the analytical results on a large network using a network-based model. Similarly, Danwen (2010) presented a multi-factor travel mode choice model that included factors of parking pricing and transit fare and identified the trends and sensitivity of people’s travel mode choices and travel demand concerning changes in parking fare and other factors. Nourinejad et al. (2014) developed a parking choice model and a traffic simulation module to investigate the impact of truck parking policy in city centres. Their results indicated that parking search time for freight vehicles was lower in the presence of on-street parking for freight vehicles, whereas the searching time and walking time for passenger vehicles were higher. As can be seen, parking policies greatly affect traffic demand and condition, and have a significant impact on the transportation system; thus, they should be carefully designed, evaluated and implemented.
In order to design and assess urban parking policies such as pricing, parking space distribution, illegal parking enforcement level, parking fine, and parking-oriented ITS, it is essential to gain a clear and valid understanding of drivers’ parking choice behaviour. Several studies have developed traffic simulation models to represent or estimate drivers’ parking search behaviour. Thompson and Richardson (1998) presented a model to determine individual driver’s choice sets endogenously, and the behavioural modelling framework is based on drivers’ experiences of parking searching. Lam et al. (2006) proposed a time-dependent traffic equilibrium model that incorporates travellers’ departure time, route, and parking-related choices. Its numerical results indicate several influential factors on parking behaviour, such as travel demand, parking capacity and pricing. The model is useful for analyzing the interaction effects between traffic flows and parking choices. With the same purpose, Leurent and Boujnah (2014) developed a network model to represent drivers’ choices on route selection and parking choice according to travel demand (origin-destination pair). The model incorporated transition probability between parking lots based on parking lot capacity and occupancy rate.

Many more studies are oriented towards identifying and evaluating the determining factors that affect parking choice behaviour, which is analyzed by estimating discrete choice models, such as nested logit model and multinomial logit model. For example, Axhausen and Polak (1991) collected drivers’ parking choice data using a stated preference approach and estimated two logit models that assess the factors that influence people’s parking choices. The study was designed to compare the two models, which grouped attributes differently, and were estimated for various trip purposes. The results indicated that the model with separate time attributes (travel time, search time and walk time) provided more accurate predictions of parking choice than the model with aggregate time variables. Thus the three time-related attributes should be separately considered in a logit model. The model also indicated a different importance level for each attribute across various trip purposes. Hunt and Teply (1993) estimated a nested logit model of parking choice using data from a RP survey, which collected data of drivers’ parking behaviour in a central business district. The estimated model considered different types of parking choices (on-, off-street, and employer arranged parking) as alternatives for the first level of the nested structure, and individual locations of each parking type were alternatives for the second level. The model also
incorporated attributes other than cost and walking distance in the utility functions, such as the relative location of parking space to destination and origin, parking capacity, etc. Golias et al. (2002) performed a SP survey and built a binary logit model to determine the factors that have influences on drivers’ parking choices between on- and off-street parking. The results indicated that the most critical impact of parking alternatives is parking cost. The rest of the attributes ranked based on the significance level were: parking search time, dwell time and walking time, respectively. The study also concluded that the trip and driver characteristics, such as age, gender, income, and trip frequency, have no impacts on the parking choices. Simićević et al. (2013) estimated multinomial logit models for two trip purposes (work and non-work trips) based on a stated preference data collection, and aimed at assessing the effects of introducing or changing the parking price and time limitation on parking choices among three alternatives (on-street parking, off-street parking, mode switch) in Belgrade, the capital of Serbia. The model results showed that parking price could affect the amount of parking demand through travel mode switch. Also, it was found that tightening the dwell time limit only affects the ratio between different parking types (on- or off-street parking), while its influence on parking demand is negligible, especially for work trips.

Chaniotakis and Pel (2015) aimed to understand the impact of parking availability on parking and estimated different types of random utility maximization (RUM) choice models based on the results from a SP survey. They concluded that parking availability after 8 minutes of searching ranks as the second most crucial factor affecting parking choices, while the availability upon arrival ranks fourth. There are many other studies that focus on identifying and evaluating the influential factors for parking choices (Gillen, 1978; Hunt, 1988; Bonsall and Palmer, 2004; Van der Waerden, 2012). The attributes from those studies and the ones discussed above are summarized in Table 1. The checkmarks indicate that the attributes were surveyed and considered in model development. The checkmarks in black indicate that the attributes have a statistically significant influence on drivers’ parking choice, and the ones in grey indicate that their influence on parking choice is negligible.
Table 1. Parking choice model attributes considered in the literature

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<tr>
<th>Study</th>
<th>Cost</th>
<th>Walking Distance</th>
<th>Travel Time</th>
<th>Search Time</th>
<th>Dwelling Time</th>
<th>Parking Type</th>
<th>Illegal Fine</th>
<th>Purpose</th>
<th>Occupancy</th>
<th>Vehicle Safety</th>
<th>Age</th>
<th>Income</th>
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2.7 Conclusion

The literature review focused on parking-related research studies about parking choice determinants and methodological contents related to the data collection and modelling of parking choices. RP survey is one of two commonly used data collection methods. The choice set for this approach is very complex and challenging to define, and it usually requires the assistance of technology. Although several studies endeavoured to solve the shortcomings of choice set identification by grouping approaches, there are still many issues with this method. On the other hand, a SP survey’s choice set can be clearly and easily defined for different scenarios, while the number of alternatives and attributes are limited.

Travel simulation has been introduced as another data collection method, which is superior to conventional RP or SP surveys because it is able to simulate the SP survey in a controlled
environment and obtain rich data with higher validity. Similar to conventional survey methods, travel simulation also needs incentives for participation motivation. Gamification is one of the three motivation types that is most effective and promising in terms of participation rate and data quality. Another advantage of a travel simulator is its capability of simulating various parking environment settings to test different parking policies and new technology applications.

Some developing parking technologies, such as PGI and parking reservation systems, are reviewed and their potential implications on the transportation system, especially for parking influences, are explored through past studies. There is a need to assess the new parking ITS applications and their interactions with parking policies. Understanding of parking choice behaviour is required, and many excellent past studies on parking choices are reviewed, and the influential factors are concluded from discussed literature.
Chapter 3 Methodology

A simulation game, called iCity Park, is designed as a SP survey to collect data about drivers’ parking choices under different scenarios, as well as their personal characteristics. The collected data need to be processed to summarize individuals parking choice and information, then logit models are constructed using the results to predict parking choice behaviours. The models include multinomial logit (MNL) models, nested logit (NL) models with different nesting structures, and mixed logit (MXL) models, and the most appropriate model structure is selected for each parking assistance level. This section presents the iCity Park survey design and the parking model estimation methods.

This chapter is organized as follows. The iCity Park survey is introduced, which includes two major parts. The first part of the survey, the virtual parking simulation gameplay explains the game’s basic settings, parking alternatives, attributes involved, scenario design and scoring systems. The next section of the survey design includes socioeconomic questions. Next, data processing explains how the data is organized and processed to prepare results that are ready for model estimation. Lastly, the discrete choice model formulation and estimation are discussed, which include model alternatives and attributes, model structures, and model comparison.

3.1 Survey Design

iCity Park is designed as a SP survey to collect data about drivers’ parking preferences under hypothetical scenarios where legal and illegal parking spots are available, and parking enforcement is present. The survey lasts approximately 13 minutes based on the pretest and comprises three sections. The first section introduces the survey and briefly explains the goals of the parking tasks. The second section is parking gameplay, which involves game instructions and 24 parking game scenarios in 2 different assistance levels, namely, the conventional parking and the assisted parking. The last section of the survey consists of a series of socioeconomic questions that collect respondents’ characteristics.
3.1.1 iCity Park Gameplay

The parking game consists of many game scenarios, and each requires players to perform a parking task in order to arrive at destinations on time. Players pay a cost for parking and receive a reward for getting to their destinations on time. They make choices between legal and illegal parking spots at different locations, considering the parking cost, parking fines, driving time, walking time and other parameters in each scenario. There are two parking assistance levels, which are conventional parking and assisted parking, and each includes 12 different scenarios, which use different combinations of attribute values. Also, the user interfaces and controls differ for the two levels. The assistance levels are explained in more detail in Section 3.1.1.4.

The terminologies used in this section are explained here to provide a better understanding of the content as the definitions are specific to the parking game. In the parking game, the choice set of alternatives refers to available parking spots which a respondent considers when choosing a parking spot. The attributes refer to the characteristics of each parking spot, such as parking rate and availability. Each attribute has different levels, which refer to the degrees of each spot’s characteristic, such as different parking rates. A specific combination of attribute levels generates one scenario.

3.1.1.1 Basic Game Settings

Road Network

The road network for the parking game is a five-by-five square grid network, with a block side-length of 300 meters, which is set based on the average block length in downtown Toronto.

Initial and Destination Locations

A five-by-five grid network is set as the road network in the parking game, and thus the destination is set on a corner of the central block for all scenarios such that drivers can cruise around the destination to find parking spots. The vehicle’s initial locations are set at one of four designated intersections that are four block-distance away from the destination. The
destination location, shown as a blue star, and start locations, indicated by red vehicles, are shown in Figure 1.

Figure 1. Destination and start locations in the road network

Parking Spot Distribution

Parking spots are distributed along the four faces of all blocks. For each block face, there are eight legal parking spots that are located in the middle and two illegal parking spots that are located close to intersections. Figure 2 illustrates the distribution of legal and illegal parking spots along the block faces.
Vehicle Driving Speed

Driving speed and parking task time limit, the given time for players to reach destinations on time, impose related influence on the process of choosing parking spots, because driving speed directly affects driving time and thus the total time used to reach destinations, which is compared to parking task time frame to determine whether they are on time. Instead of making players experience different driving speed and resulting driving time for each parking spot, only parking task time frame are varied and set as time limits, which have impacts on drivers’ parking choices. Therefore, traffic condition setting is abandoned, and a typical average driving speed in Toronto downtown is used, which is approximately 25 km/hour (Toronto downtown average vehicle speed in 2014) (Matthias et al., 2015).

Walking Speed

Although walking speed varies individually, the parking game considers an average walking speed to limit the number of variables. The average walking speed of pedestrians is affected
by several factors, such as age, gender, and group size. There are many studies that have evaluated pedestrians’ walking speeds for transportation operation design and policymaking, such as road width and traffic signal timing. For example, Tarawneh (2001) evaluated the influential factors of walking speed in Jordan, and the results recommended an average walking speed of 1.11 m/s for traffic signal designs, which was the 15\textsuperscript{th}-percentile walking speeds of 3500 pedestrians. Knoblauch et al. (1996) conducted a similar study on pedestrian speeds. The results showed that the average speed was 1.22 m/s for younger pedestrians and 0.91 m/s for older pedestrians. The average speeds from both studies are crossing speeds at signalized intersections, and thus the normal average speed is lower since pedestrians tend to walk faster when crossing roads. Consequently, the parking game sets one meter per second as average walking speed to compute the walking time from parking spots to destinations.

### 3.1.1.2 Parking Choice Alternatives

The parking game is designed as a SP survey. The choice set consists of seen parking spots for the conventional parking and all available parking spots for the assisted parking. The legal or illegal parking spots along the same block face are similar because their attributes are set with the same level, although there are small variations across different spots within a block face in driving and walking times. Consequently, the choice set of the parking game is grouped and categorized based on parking spots’ types and locations. The small variations across spots within a block face are ignored.

There are five parking alternatives in the game, which are located in different parts of the network. They are designed as labelled alternatives since their names have special meaning to the players, such as legal and illegal parking. The first and second alternatives are the legal and illegal parking spots within one block-distance to the destination (in red region) in the road network, respectively. The parking spot distribution leads to a diamond shape, which is also the result of the grid system of streets. The third and fourth alternatives are legal and illegal parking spots that are within a two-block-distance but outside one-block-distance to the destination (in the grey region), respectively. The last alternative includes parking spots that are more than two blocks away from the destination. The attribute levels are varied between alternatives that are in different diamond shapes, and thus respondents’ choices are
able to reflect the influential power of the designed attributes. The attribute level variation is described in the scenario design section.

![Figure 3. Parking alternative regions](image)

3.1.1.3 Attributes and Attribute Levels

A large number of attributes leads to an increased number of scenarios required to capture the impacts of each attribute and may cause player fatigue and thus low-quality data. Consequently, for each scenario, there are only six attributes that characterize the parking spots, which are parking dwell time, time limit, legal parking fare, occupancy level, citation probability per hour, and illegal parking fine. The six attributes are selected based on the
literature review of studies that focus on parking choice modelling, and these attributes are found to be statistically significant in influencing parking choices in the reviewed studies (Hunt, 1988; Axhausen and Polak, 1991; Golias et al., 2002; Van der Waerden, 2012; Simićević et al., 2013). Each attribute is designed to have two levels assuming that the model is linear for all attributes (Molin, 2011). This is similar to Chaniotakis & Pel (2015) who constructed a parking choice model from the data collected in a SP survey that includes attributes of parking cost, walking time, driving time, and occupancy. They assumed that all of these attributes have two levels. Golias et al. (2002) also used two attribute levels for the walking time from parking spots to destinations in a SP survey. Although some other studies used more than two attribute levels for parking cost, walking and driving time, occupancy and other factors to test their sensitivities, more attributes are considered in the iCity Park game, and thus each attribute is limited to two levels to shorten the total survey time. The ranges of the attributes are chosen based on their values in reality (i.e. the context of Toronto downtown). Some of them are adjusted to obtain a wider range, which is statistically preferable to using a narrow range for better parameter estimations (Rose & Bliemer, 2009). Each attribute is described below in detail, and a summary is presented in Table 2.

- **Dwell Time Levels**
  The lower and higher levels of parking dwell times are 30 and 60 minutes, respectively. Although most on-street parking in Toronto has a time limitation of 3 hours, shorter dwell times are selected. Drivers tend to park for a short period that’s less than the limit if they choose on-street parking. Also, the parking game seeks to observe drivers’ parking decisions with the presence of illegal parking, and the impression of short dwell time can make drivers subconsciously consider illegal parking. Therefore, the dwell times are set in the lower range of parking time limitation, which are 30 and 60 minutes.

- **Parking Task Time Limit Levels**
  The lower and higher level of parking task time limit, which is the time frame for respondents to complete a parking task and arrive at their destinations on time, are 10 and 15 minutes, respectively. The lower and higher values are chosen such that drivers can arrive at destinations on time only if they choose parking spots that are
within one or two block-distance to the destination, respectively. Consequently, alternative five, which includes parking spots that are more than two-block-distance away from destinations, would never be on time. The time frames limit players’ parking choices within the outer diamond boundary if they want to arrive at destinations on time, and the boundary provides a complete and symmetric road network.

• Legal Parking Rate Levels
The lower and higher levels of legal parking rates are 4 and 10 dollars per hour, respectively. On-street parking rates in Toronto range from 1 to 4 dollars per hour (City of Toronto-a, 2018), and most parking spots have a rate of 3 dollars per hour. Using the average parking rate, the total cost of on-street parking ranges from 0 to 9 dollars based on the parking time limitation of 3 hours. The parking rates in the parking game are set such that the total cost in the game is approximately the same as the total cost in real life, and the rates have a reasonably wide range without causing dominating alternatives. Accordingly, the parking rates in the parking game are set to 4 and 10 dollars per hour.

• Legal Parking Occupancy Levels
The lower and higher levels of parking occupancy levels are 0.8 and 0.95, respectively. The occupancy levels should be set to vary parking supply and affect parking choices. The streets with high occupancy level should provide few or no vacant parking spots, and the streets with low occupancy level should provide a limited number of vacant spots. The occupancy levels were tested many times and accordingly set to 0.8 and 0.95.

• Illegal Parking Citation Probability Levels
The lower and higher levels of illegal parking citation probabilities per hour are 0.4 and 0.8, respectively. The illegal parking citation probability is calculated according to the patrolling frequency of enforcement units in a region, and thus it is not a stochastic process. For example, if it takes 2 hours for an enforcement unit to patrol
its jurisdictional region, the citation probability for that region would be 50 percent per hour. Furthermore, the final citation probability depends on parking dwell times. Based on the dwell time setting in the game, the citation probabilities are designed to have a wide range, from 20 to 80 percent, and the highest probability is lower than 100 percent to make illegal parking always an alternative in the game.

- Illegal Parking Fine Levels
  The lower and higher levels of illegal parking fines are 40 and 100 dollars, respectively. There are many different types of parking offences that receive fines. For example, in GTHA, fines are issued if a vehicle parks longer than 3 hours, obstructs driveway/laneway, parks within 3 meters of a fire hydrant, etc. (City of Toronto-b, 2018). Although the parking fine ranges from $30 to $450, more than 84 percent of the illegal parking receives fines that are lower than $100 in the City of Toronto in 2016 (Treasurer, 2017). To make the illegal parking fine more realistic, the low average fine of $40 is selected as the lower fine level because half of the offences that can be issued fines range from $30 to $60, and $100 is set as the higher fine level which is the highest parking fine drivers are usually charged.

Table 2. Attributes and attribute level summary

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Lower Level</th>
<th>Higher Level</th>
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<td>Dwell Time [min]</td>
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<tr>
<td>Parking task time limit [min]</td>
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</tr>
<tr>
<td>Legal Parking Rate [$/hour]</td>
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<td>10</td>
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<tr>
<td>Legal Parking Occupancy</td>
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<td>0.95</td>
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<tr>
<td>Illegal Parking Citation Probability [/hour]</td>
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<td>0.8</td>
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<td>Illegal Parking Fine [$]</td>
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</table>
3.1.1.4 Parking Assistance Levels

There are two assistance levels in the parking game, which are the conventional parking and the assisted parking. In the conventional parking, as shown in Figure 4, players can only observe states of parking spots around their current location with a limited distance. In this level, respondents are first informed about the parking time frame for their parking tasks and the dwell time. Then they need to use arrow keys to direct vehicles to intersections in the five-by-five grid network and approach destinations. Only parking spots that are within one block-distance from the vehicle’s current location are visible, these spots’ information can be viewed, and any spot can be selected to park. On the other hand, players can observe states of all parking spots in the network in assisted parking, which is shown in Figure 5. This level intends to simulate parking tasks with the help of parking guidance and information systems. Similar to the other level, parking tasks are first given before each scenario. Then players can view the whole network and zoom into blocks to view parking spots in these blocks. Consequently, the parking spot availability, parking rates, arrival time, driving and walking time, and other parameters of all spots in the network are known at the beginning. Finally, players will choose one spot to park, and the vehicle will be directed to the selected spot using the shortest path.

The two parking assistance levels represent different parking circumstances. The conventional parking simulates conventional parking behaviour, where drivers have to cruise around their destinations to check parking information, such as availability, and parking fare. The assisted parking is a representation of parking with the assistance of PGI and parking reservation systems because drivers can obtain parking and arrival information from the intelligent parking system, and make parking decisions and reservations before departure.
Figure 4. Conventional parking user interface

Figure 5. Assisted parking user interface
3.1.1.5 Fractional Factorial Scenario Design

A fractional factorial design was implemented to create scenarios. This design is generated using a simultaneous choice set creation method, also called $L^{MN}$ design method, which preserves the orthogonality of the attributes both within and between the alternatives (Molin, 2011). Furthermore, the attribute level balance property is carried out in the design process, meaning that each attribute level appears an equal number of times for each attribute. This property ensures that the parameters can be estimated well on the whole range of levels, and avoids attribute levels with missing data points.

The six attributes are involved in the scenario design, and some of them are alternative specific attributes. For example, dwell time and parking time frame are two alternative specific variables (ASVs) since their values are the same across all alternatives. On the other hand, legal parking rate, occupancy level, citation probability and parking fine are generic attributes because their values vary across different alternatives. Using the method of simultaneous choice set, there are ten attributes in one scenario, and each attribute has two levels. IMB SPSS software is used to generate the orthogonal fractional-factorial design with the minimum number of scenarios, and the resulting attribute level table is shown in Table 3. In the attribute level table, attribute levels are varied across 12 scenarios, and “0” represents the lower level of attributes and “1” represents the higher level of attributes. Only four alternatives are considered in the scenario design. For the fifth alternative, parking spots that are more than two block-distance away from the destination, are not included since it is not able to fulfil the goal of reaching destinations on time, and the parking spots or the network in the alternative is not symmetric around the destination. Consequently, the fifth alternative is considered to be infeasible and game scenarios are ignored if it is chosen in the survey.

The gameplay contains 12 game scenarios for each parking assistance level, resulting in 24 scenarios in total. However, survey fatigue is anticipated and observed during the pretest. Survey fatigue may cause poor data collection since respondents can quickly get tired of trying to select their actual preferred parking spots. Also, it may lead to high rates of abandonment in the halfway of the survey. Therefore, the number of game scenarios in the survey is reduced to make it respectful of respondents’ time and obtain better data quality. Four relatively or weakly dominant scenarios (scenarios 8, 9, 10, and 12), as compared to
others based on attribute levels, are selected and deleted in the survey. The weakly dominant scenarios mean that their alternatives yield better payoff than the same alternative in their dominated scenarios. For example, a dominant scenario or scenario has a lower legal parking rate than its dominated scenario, with all other attribute levels being the same or similar. In order to preserve the orthogonality and attribute level balance property in the original fractional-factorial design, respondents’ choices for those four scenarios are anticipated based on their choices for other scenarios, and they are used in model estimation. Specifically, results from scenarios 2, 3, 5 and 7 are used to predict respondents’ choices for scenarios 8, 9, 10, and 12, respectively. Those dominated scenarios (2, 3, 5 and 7) are chosen because their attribute levels are similar to the relatively dominant scenarios, with one or two different attribute values, which make the dominated scenarios’ alternatives relatively competitive than the reduced ones. As a result, the survey has eight fewer scenarios, which substantially mitigates the survey fatigue.

The scenario design intends to collect data to support the evaluation of influential factors that have impacts on parking choices. The same scenarios are used for both assistance levels to investigate the influences of PGI and parking reservation systems.
### Table 3. Scenario design table

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<thead>
<tr>
<th>Scenario</th>
<th>Dwell time</th>
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<td>0</td>
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</tr>
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<td>1</td>
<td>0</td>
<td>0</td>
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</tr>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

### 3.1.1.6 Scoring System

A scoring system is designed to provide feedback to respondents’ parking performance. It works as an aspect of gamification incentive, which replaces extrinsic (monetary) incentives, to motivate players to make parking choices as they would in real life. A score bar, which is placed on the top part of the user interface, is used to show the current score and some score thresholds. The thresholds are shown as stars that can be obtained by reaching certain score levels, and the number of stars earned at the end of the game reflects users’ parking performance.

The initial score is set to 500 dollars to provide players with a sufficient fund to pay for an illegal parking fine if they get cited. In each scenario, there is a cost and a reward for arriving
at the destination on time. The cost is simply the parking cost. For legal parking, the possible total cost for one scenario could be 2, 4, 5, or 10 dollars, which depends on the dwell time and parking rate. There is no cost for parking illegally if it is not cited by patrolling enforcement units. To motivate players to reduce parking cost as they would in real life, the reward for each scenario is set such that there is only a small net increase in score or no net increase at all if they do not consider the cheapest legal parking spots or illegal parking. Therefore, the rewards are set as 5 dollars for scenarios with low dwell time level and 10 dollars for scenarios with high dwell time level if players arrive at destinations on time. In order to achieve maximum score or certain score thresholds, players have to consider parking with the lowest parking rate or illegal parking, and most importantly, arriving at destinations before the time constraints to obtain rewards.

3.1.2 Questionnaire - Socioeconomic Questions

The second part of the survey is a questionnaire, which is designed to collect socio-economic information on the characteristics of respondents. According to theoretical expectations and literature review on parking-related choice surveys (Golias et al., 2002; Simićević et al., 2013; Habib et al., 2013; Chaniotakis et al., 2015; ), potential variables that may influence drivers’ choices are selected. The variables that are included in the questionnaire are age, gender, occupation status and category, education level, household information, usual travel mode, parking frequency, parking purpose, relative walking speed and income.

The questionnaire consists of 17 multiple-choice questions, including some open-ended choices and questions to gather the respondents’ socioeconomic information. The information collected through the questionnaire can be used to reveal the dependency of parking behaviour on personal characteristics.

3.1.3 Survey Database

iCity Park saves respondents’ data in a database while they are completing the survey. The database is saved as csv files to record specific game settings and all decisions made by respondents. The questionnaire results are saved in the same format.
For the gameplay part, each scenario has a corresponding csv file. The database records both basic game settings and players’ parking decisions. The saved game settings include all parking spots’ location in x-y coordinates, parking spot availability, driving and walking time for each spot, occupancy level, legal parking rate, parking fine, and citation probability for illegal parking. The user decisions include viewed parking spots with viewing duration to distinguish viewed and accidentally rollover parking spots, time spent to make final parking decisions, selected parking spots, dwell time and time constraint for each scenario, total parking cost, whether the players arrive at destinations on time or late, and the resulting score at the end of each scenario. Furthermore, in conventional parking, the driving routes directed by players to approach destinations are saved as successive intersection coordinates with time stamps.

For the questionnaire part, the choices selected by respondents are saved for all multiple-choice questions, and general comments in text form are saved as well.

### 3.2 Data Processing

The raw data collected from the survey needs to be processed and analyzed for model estimation. Some attributes used in parking models need to be computed using several saved variables, and selected parking spots need to be classified into designed alternatives. This section describes how the data were prepared for model estimation.

#### 3.2.1 Parking Access Time

The period from the beginning of each scenario to parking completion on the selected parking spot is parking access time and is determined by search and driving time in the survey. Search time is the time spent to make parking decisions, which includes checking parking spot information. Driving time is the time used to direct the vehicle from its initial location to the final parking spot along routes selected by players, which may not be the shortest path between the two locations. The parking access time and driving time are recorded in the database, then the search time can be computed by subtracting the driving time by total access time for each game scenario.
3.2.2 Defining Choice Set and Computing Alternative Attributes

Most attributes of parking spots in each alternative have the same generic attribute level. For example, the citation probability and fine are the same for all illegal parking spots in each illegal parking alternative, and the parking rate and occupancy level are the same for all legal parking spots in each legal parking alternative. However, some attributes are spot specific, meaning that each spot has different attribute values even when they are in the same alternative, such as driving time and walking time. Therefore, those attribute values need to be approximated for all alternatives.

To compute average attributes for each alternative, its available parking spots, which are vacant parking spots seen by respondents, should be defined first. The feasible parking spots for different assistance levels are different. For conventional parking, all available parking spots along the routes that vehicles are cruising are the feasible parking spots. The feasible parking spots for assisted parking consists of all available parking spots in the road network. Therefore, the feasible parking spots for all scenarios need to be defined, and their attributes’ values are used to approximate the attributes of designed alternatives.

The feasible parking spots can be classified into several groups based on their locations and types according to design alternatives. Then the attributes of feasible parking spots in each alternative are averaged to represent the alternative’s attribute values, such as driving time and walking time. For the assisted parking, drivers tend to park in streets that are on their paths to the destination, not to choose streets with the same attributes that are farther than the destination, because they can view all the parking spots in the symmetric network around the destination. As a result, for the assisted parking, the feasible parking spots that are used to compute average driving and walking time should only include available parking spots in a half diamond-shape region that is close to origins in each alternative region. Also, the viewed or clicked parking spots by respondents are considered and can be used to compute average alternative attributes directly if the number of viewed spots is sufficiently large. For conventional parking, the nodes that are visited indicate drivers’ routes used to approach the destinations, so parking spots on the streets that are connected to the nodes are considered viewed spots by the drivers. Therefore, those parking spots form feasible parking spots, and they are further classified by alternatives to compute the averaged attributes.
Accordingly, the average alternative attributes, driving and walking time, are computed using each alternative’s corresponding feasible parking spots, and the values are used in model estimation.

3.2.3 Parking Alternative Classification

The specific parking spots selected by respondents are saved in the database, and they are classified into designed alternatives according to their locations and types. Individual parking spots cannot be treated as one alternative, because it would lead to a large number of alternatives, which adds difficulties to run the survey and build models. First, increasing the number of alternatives increases the number of attribute level combinations in a full-factorial design. Thus it also exponentially increases the minimum number of scenarios for fractional-factorial design, meaning an extended time to complete the survey. Second, parking spots that are close to each other or on the same street have similar attributes, such as driving and walking times, parking rates and occupancy level, so it would be difficult to observe each attribute’s influential power on parking choice during model estimation. Consequently, parking spots are categorized into four alternatives, and the parking result in each scenario is classified.

3.3 Discrete Choice Model Formulation and Estimation

Discrete choice modelling is used to capture and evaluate the influential factors for on-street parking choices. In this section, the model structure and formulation using random utility theory are presented. The random utility theory (RUT) and development of logit model formulation described by Ben-Akiva and Lerman (1985) are used for the parking choice models.

The data collected from iCity Park survey are used to develop three types of parking choice models, nested logit (NL) model, multinomial logit (MNL) model and mixed logit (MXL) model. The alternatives and attributes considered in the models are described first, then the potential model structures that are tested are discussed in this section.
3.3.1 Alternatives and Attributes

There are five alternatives designed in the iCity Park game section, while only four of them are considered in model estimation. The four alternatives are legal and illegal parking spots that are within a two block-distance from destinations, and parking spots that are farther away from destinations, which are categorized into alternative five, are not considered valid since respondents cannot arrive at destinations on time if they park in these spots. Therefore, only four alternatives are used to develop parking choice models.

Discrete choice model development requires some attributes to characterize each alternative, and six generic variables and one ASV are proposed. The generic attributes are average driving time, average walking time, legal parking cost, legal occupancy level, illegal citation probability and illegal parking fine. Parking cost and citation probability have taken dwell time into account. These parameters are generic because their values are different across alternatives, and thus they have the same parameter. The alternative specific attribute is parking task time limit. The variable is alternative specific because it is the same in one game scenario and thus the same for all alternatives.

Other than the attributes that are varied in the game settings, respondents’ characteristics that are collected in the questionnaire section of the survey. Some of the collected socioeconomic information on the characteristics of respondents are expected to have influences on their parking choices. They are introduced into the utility functions for testing as ASVs In model estimation, the number of each ASV in the utility functions should be less than the number of alternatives. Therefore, each ASV is introduced into each alternative’s utility function by a specific parameter that times the ASV, with one of the parameters fixed to zero in an alternative’s utility function. Then the model can be improved by testing and eliminating parameters of ASVs based on their statistical significance. To start adding one ASV in the utility functions, the parameter value is fixed for one alternative. In this case, only three alternative’s utility functions have the new added ASV since there is a total of four alternatives. Next, the estimated parameters for the ASV are evaluated based on their signs, magnitude, and t statistic values of corresponding variables (if it is a vital policy variable, keep it even with low t-statistics), and some of them can be eliminated for better model fit. In the end, if the ASV still appear in the utility functions, it indicates that it has influence on
parking choices among the alternatives. Each ASV’s effects on different alternatives can also be revealed according to the variable’s location in the utility functions. For example, if one ASV appears only in illegal parking alternatives’ utility functions, it indicates that people with the corresponding characteristics favour or dislike illegal parking based the signs of the parameters. Section 4.2.1 analyzes collected demographic attributes that are tested during modelling and discusses how they are introduced into the utility functions.

3.3.2 Model Structures

In the parking game, respondents are assumed to draw utility from selecting an alternative from one of the SP scenarios. The utility function (U) for each alternative consists of systematic (V) and random (ε) components. The systematic utility function is a linear-in-parameter function of the attributes (x) and corresponding coefficients (β), and it describes the deterministic utility of choosing an alternative. The random component explains the unobserved random variations in parking choices.

\[ U_i = V_i + \varepsilon_i = (\beta x)_i + \varepsilon_i \]

Where the subscript i indicates one of the four alternatives.

The random component is assumed to be IID (independent and identically distributed) and type I extreme value (Gumbel) distributed with a location parameter of \( \eta=0 \), which represents the mode of distribution, and a positive scale parameter of \( \mu \), which defines the dispersion of the probability density function (PDF). Type I distribution is a common and the most convenient distribution to derive choice probability models with a closed form. With the utility functions and the assumptions, MNL and NL models, as closed-form models, can be formulated and estimated for parking choices. Consequently, the IID assumption derives the property of independent of irrelevant alternatives (IIA). A mixed logit (MXL) model is also estimated to account for the heterogeneity among respondents of the perception and preference of parking spots. The MXL model is based on the formulations of the MNL model, with random parameters or an additional random error term in the utility functions.
The utility functions for the four alternatives in the parking choice models are thus formulated as follows, and the alternative specific constant (ASC) and ASVs are fixed to 0 for alternative 1.

Table 4. Proposed utility functions for four parking alternatives

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Utility Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$V_1 = ASC_1 + \beta_{dt} \times DT_1 + \beta_{wt} \times WT_1 + \beta_{pr} \times PR_1 + \beta_{or} \times OR_1 + \beta_{tl} \times TL$</td>
</tr>
<tr>
<td>2</td>
<td>$V_2 = ASC_2 + \beta_{dt} \times DT_2 + \beta_{wt} \times WT_2 + \beta_{cp} \times CP_2 + \beta_{fp} \times FP_2 + \beta_{tl} \times TL$</td>
</tr>
<tr>
<td>3</td>
<td>$V_3 = ASC_3 + \beta_{dt} \times DT_3 + \beta_{wt} \times WT_3 + \beta_{pr} \times PR_3 + \beta_{or} \times OR_3 + \beta_{tl} \times TL$</td>
</tr>
<tr>
<td>4</td>
<td>$V_4 = ASC_4 + \beta_{dt} \times DT_4 + \beta_{wt} \times WT_4 + \beta_{cp} \times CP_4 + \beta_{fp} \times FP_4 + \beta_{tl} \times TL$</td>
</tr>
</tbody>
</table>

where

$V$: alternative utility function

$\beta$: coefficient

$ASC$: alternative specific constant

- Alternative specific variables:

$DW$: dwell time

$TL$: parking time limit (frame)

- Generic variables:

$DT$: driving time

$WT$: walking time

$PR$: parking cost for legal parking

$OR$: occupancy rate for legal parking
CP: citation probability for illegal parking

FP: fine for illegal parking

3.3.2.1 Multinomial Logit (MNL) Model

The assumption that random utility terms are Gumbel distributed with location parameter \( \eta = 0 \) and a common scale parameter leads to a multinomial logit (MNL) model, and Equation 1 shows the probability function for the alternatives. MNL model allows a choice between multiple (greater than 2) alternatives. The proposed parking MNL model structure is shown in Figure 6.

\[
\text{probability} \ (i) = \frac{\exp(\mu V_i)}{\sum_{i' = 1}^{I} \exp(\mu V_{i'})}
\]

[1]

Where the subscript \( i' \) indicates any alternative, and \( I \) indicates the number of alternatives, which is four in this case.

![Figure 6. Proposed multinomial logit (MNL) model structure](image)

For the multinomial logit model, maximum likelihood estimation is used for parameter estimation. Then Equation 1 can be used to compute the probability of choosing each alternative.
3.3.2.2 Nested Logit (NL) Model

As compared to the MNL model, the NL model partially relaxes the assumption of IID and IIA property of MNL model by considering correlations among alternatives in nesting structures (Manski & McFadden, 1981; Train, 2003), meaning the alternatives are partitioned into nests. In this case, the IIA property holds among the alternatives in the same nest, while it does not hold for alternatives across different nests. Therefore, the NL model overcomes the limitations of the MNL model, and it can more accurately reflect people’s choice behaviours when the alternatives can be grouped into subsets.

The structure of the NL model is shown in Figure 7, followed by its resulting formulation that’s used to derive the NL model. The equations include utility functions and probability functions for upper and lower levels of the nested structure.

![Figure 7. Structure of nested logit model](image)

Lower level conditional utility function:

\[
U_{m|d} = V_{m|d} + \varepsilon_{m|d}
\]  \[2\]

Upper-level unconditional utility function:

\[
U_d = V_d + (V_{m|d} + \varepsilon_{m|d}) + \varepsilon_d = \tilde{V}_d + \varepsilon_d
\]  \[3\]
Upper level compounded systematic utility function:

\[ \tilde{V}_d \approx V_d + (V_{m|d} + \varepsilon_{m|d}) \]  

[4]

Where

\[ \varepsilon_d \approx \text{IID extreme value with scale } \mu_d \]

\[ \varepsilon_{m|d} \approx \text{IID extreme value with scale } \mu_m \]

Probability function of choosing m for a given d:

\[ \Pr(m|d) = \frac{\exp(\mu_m V_{m|d})}{\sum_{m \in M} \exp(\mu_m V_{m|d})} \]  

[5]

Probability function of choosing d:

\[ \Pr(d) = \frac{\exp(\mu_d V_d + \frac{\mu_d}{\mu_m} \ln(\sum_{m \in M} \exp(\mu_m V_{m|d})))}{\sum_{d \in D} \exp(\mu_d V_d + \frac{\mu_d}{\mu_m} \ln(\sum_{m \in M} \exp(\mu_m V_{m|d})))} \]  

[6]

And

Define, \( \emptyset = \frac{\mu_d}{\mu_m} \)  

[7]

\[ 0 < \emptyset < 1 \]  

[8]

\[ \Pr(m) = \Pr(d) \times \Pr(m|d) \]  

[9]

To make sure the NL model is consistent with random utility maximization (RUM) choice model, the scale of the lower-level conditional choice should be larger than the scale of upper-level choice (Manski & McFadden, 1981), which means that the value of \( \emptyset \) should be between zero and one. \( \emptyset \) is known as inclusive value or Logsum parameter, and it can be considered as a measure of dissimilarity among alternatives (Qin, et al., 2017). In Biogeme
modelling, the upper-level scale factor \( (\mu_d) \) is normalized to one, thus the lower-level scale factor \( (\mu_m) \) has to be greater than one.

A NL model is used in some studies for analyzing parking choice behaviours. Some of the studies partitioned the nests based on parking locations (Qin, et al., 2017), while others considered parking spot types in the nesting structure (Hunt & Teply, 1993). Therefore, two nested logit model structures are proposed. The first one groups alternatives according to their relative distance to destination into two nests. The upper level contains two nests, which specify the parking locations and are named as inner parking region and outer parking region. Each nest contains two alternatives, which are legal and illegal parking spot in that region. The second nested structure also has two nests, legal parking and illegal parking, which is constructed based on the parking spot types. Similarly, there are two alternatives in each nest. The proposed nested structures are shown in Figure 8. The proposed nesting structures can also be modified by breaking one of the two nests in modelling test because the respondents’ parking behaviours may not reflect both nests.

![nested structure concerning parking locations](image)
3.3.2.3 Mixed Logit (MXL) Model

MNL model assumes that observations from the same respondent are independent of each other, while some individuals of the respondents may have parking spot preferences. For example, some individuals may prefer to park legally or illegally, and some may prefer parking spots that are close to the destination regardless of the parking types. The unobserved effects that have influences on parking choices vary across individuals, and the bias can affect the accuracy of estimated parking choice models. Therefore, MXL model can be used to deal with individual preferences.

Mixed logit (MXL) model was introduced initially by Geweke et al. (1994) to account for the panel effects since the method allows for a random distribution of tastes across respondents. It is named mixed logit because the mixture of logits and probability density functions forms the choice probability. There are two types of methods to incorporate MXL models based on MNL model, and they are named as error components approach and random parameter specification. Both methods are explained, and their formulations are shown below.

The first method is error components approach, and it captures the unobserved effects by adding a separate error component in the random component. The new utility function has the following form:
The new utility function adds a random error term ($\eta$) with zero mean and a general distribution in addition to the original formulation. The probability density function of $\eta$ is denoted by $f(\eta|\Omega)$ where $\Omega$ are the fixed parameters of the distribution. Since the remaining error term ($\varepsilon$) is still assumed to be IID extreme value distribution over alternatives, the conditional choice probability (Equation 11) is logit with a given value of $\eta$. The unconditional choice probability, as shown in Equation 12, is the MNL formula integrated overall values of $\eta$ weighted by the density of $\eta$.

$$L_i(\eta) = \frac{\exp(\beta x_i + \eta)}{\sum_{i=1}^{I_i} \exp(\beta x_i + \eta_i')}$$

$$P_i = \int L_i(\eta) f(\eta|\Omega)d\eta$$

The second method is the random parameter specification, which assumes that each generic variable’s parameter, $\beta_i$, varies across respondents to accommodate their preference heterogeneity. The corresponding utility function is shown in Equation 13.

$$U_i = V_i + \varepsilon_i = (\beta' x)_i + \varepsilon_i$$

The utility function is the same as the original one, except that the parameters, $\beta'$, are random with a mean value and a general distribution that can be estimated. The probability density function of $\beta'$ is denoted by $f(\beta'|\Omega)$ where $\Omega$ are the fixed parameters of the distribution. The unconditional choice probability function for the random parameter method is shown below.

$$P_i = \int L(i) f(\beta'|\Omega)d\beta'$$

And

$$L(i) = \frac{\exp(\beta_i x_i)}{\sum_{i'=1}^{I_i} \exp(\beta_i x_i')}$$

The two methods have different approaches to incorporate random terms, while their estimation outcomes are identical since the standard deviation of a random parameter is
equivalent to an additional error term (Hensher & Greene, 2003). In this case, the error components approach method is utilized to formulate the MXL model for the parking choices. Error components approach is more convenient than the other method because it only requires adding one random error term in each of the four utility functions. In comparison, the random parameter method assumes all parameters are random, which makes the utility functions complicated because there are many generic variables, and some of them only appear in specific alternatives in the parking spot utilities.

The two methods of MXL models both use random terms that have mean values with general distributions to capture the panel effects across individuals, and the most popular distributions are normal, triangular, uniform and lognormal. Normal distribution is selected to estimate random error components in the utility functions. First, normal distribution, as an unbounded distribution, allows both positive and negative values being added into utility functions. It is more realistic than bounded distribution in terms of anticipating individuals’ preferences over alternatives, which can be positive or negative (Jiang et al., 2018). Also, Hess et al. (2005b) demonstrated that a mixed logit model using unbounded distribution (i.e. normal distribution) always has a better fit than the model with bounded distributions. Lastly, there are many studies that estimated MXL models based on data from SP surveys using normal distributions, and all the models resulted in better fit than other types of distributions (Hess & Polak, 2005a; Yáñez et al., 2010; Brownstone et al., 2000; Jiang et al., 2018; Lovreglio et al., 2016).

MXL model is considered to be superior to the conventional MNL model since MXL model handles panel effects in a general approach and avoids MNL model’s unrealistic assumptions. In terms of capturing the unobserved heterogeneity, although the conventional discrete choice models can accomplish it through data segmentation, meaning estimating different models for different variable ranges, this method has drawbacks. It is challenging to select the appropriate segmentation criteria and be certain that the unobserved effects are accounted by the ranges. In contrast, the method that MXL model deals with the preference heterogeneity is general. Also, MXL model avoids the unrealistic assumptions of IID and IIA property, because it is able to account for the preferences of individuals.
The MXL model also has shortcomings, and one of them is that the unconditional probability formula does not have a closed-form expression. As shown in Equation 12 and 14, both approaches of MXL model lead to choice probability formulas that involve integrals, which represent that they do not have closed-form expressions. In this case, the probability of choosing each alternative can only be approximated through simulation, using Monte Carlo Techniques (Train, 2009; Hess et al., 2006).

Therefore, in order to accommodate the presence of preference heterogeneity in the sampled population, which is referred as the panel effects or unobserved heterogeneity, a random error component is incorporated into the utility functions to capture the stochastic effects. The standard deviation of the random error components is estimated by assuming a normal distribution, and they vary across respondents but does not vary across observations from the same respondents.

3.3.3 Model Comparison

The proposed three logit models (one MNL and two NL models) are estimated for each parking assistance level, resulting in six models. Each model describes the influential factors that affect parking choices and the probability of selecting each alternative. These models are then compared to each other to justify model structures and compare the influential power of the attributes across parking assistance levels, which explains the implications of parking technology applications (i.e. PGI systems) on drivers’ parking behaviour.

First, the two NL models with different nesting structures are compared to check which nesting structure is appropriate or has stronger correlations. First, the two NL models are tested using utility functions that only include ASCs to test which model structure is appropriate. The lower-level scale factor ($\mu_m$) from the modelling results should be higher than one to prove that the model structure suits the data. On the other hand, a model structure whose results have the lower-level scale factor ($\mu_m$) smaller than one should be abandoned. If the ASC modelling tests could not eliminate one of the NL model structures, the goodness-of-fit is used to compare the two models. The model with better goodness-of-fit means that the nesting structure is more appropriate than the other, and proves that the respondents made the same sequence of choice in selecting parking alternatives as to the nesting structure.
Second, for each parking assistance level, the MNL model and NL model are compared. Statistical significance (t-statistics > 1.64) is used to justify the nesting model structure. If NL model fits the data, it means that NL model is more appropriate than MNL model due to the improvements of relaxing the assumption of IID and IIA property. Then the model coefficients could be compared to explain how respondents evaluate the influential factors across the two models and how the NL model reveals more realistic parking choices if it is justified.

The estimated MXL models are then compared to the conventional MNL models. If the MXL models provide improved fits over MNL models, it demonstrates that respondents’ preference heterogeneity is significant, and it has effects over the parking choice processes. Then the parameters of the added random error components’ distribution can be further evaluated.

Lastly, the models for conventional parking and assistance parking levels are compared. The conventional parking represents the conventional parking behaviour, where drivers cruise to gather parking information and make parking choices; while the assisted parking simulates parking with the assistance of parking technologies, such as PGI and parking reservation systems, where drivers select parking spots prior to their arrivals with full parking information. Therefore, the comparison of the two assistance level models is able to evaluate the influences of new parking technologies on people’s parking strategies. Potential benefits of parking technology applications can also be evaluated based on the collected data, such as parking decision-making time, driving and walking time. Then these data can be analyzed to evaluate the implications on local traffic around destinations and parking usage efficacy.
Chapter 4 Data Collection and Analysis

This section describes the survey implementation, including how and where the survey was conducted, potential respondents and sample size. Then the collected data are processed, and analysis of parking choices and socio-economic characteristics of respondents is performed.

4.1 Survey Implementation

iCity Park survey is an application that is installed and run on a PC or a MAC. The survey application records all decisions made in the parking game, such as selected parking spot’s location, time stamps, arrival time at the destination, view duration of each parking spot, and route used to direct the vehicle in each game scenario. Then choices or input text in the questionnaire by respondents are also recorded. The saved database can facilitate subsequent analysis, and the resulting regression models allow for a detailed understanding of parking decision-making process.

The iCity Park survey was conducted at University of Toronto and OCAD University in June 2019, in accordance with an approved survey ethics protocol from the research ethics board at University of Toronto. Survey respondents were mainly recruited in faculty computer labs. It was also advertised via invitation emails containing an application download link. Survey respondents include undergraduate and graduate students, and faculty members at the two universities. Sixty-eight respondents successfully completed the survey, and the data include 793 valid observations for conventional parking and 798 for assisted parking. This sample size is considered sufficient to meet the requirements of regression modelling.

4.2 Survey Data Analysis

Univariate analysis is first conducted for several socioeconomic factors, such as respondents’ gender, age, and parking frequency. The descriptive analysis provides an overview of the characteristics of the respondents, and they are added to the proposed utility functions during model testing. Then the parking choices are classified, and the frequency distributions are presented for different levels of other variables, such as gaming level, game scenario and gender. The frequency analysis reveals various groups of respondents’ parking preferences among the four alternatives in different circumstances.
4.2.1 Respondent Socio-economic Characteristics

The iCity Park survey collects data from 68 participants, while the data from 67 respondents are considered to be valid. Among all the respondents, 40 (59.7%) are male, and 27 (40.3%) are female. Gender is expected to affect drivers’ parking choice behaviour, so it is introduced into the model estimation. A gender dummy variable is added into the proposed utility function, and it is set to 0 for men and 1 for women. The dummy variable can be tested as ASV alone, or interacted with other variables that have high statistical significance for better parameter performance.

The demographic questions collect respondents’ age groups because the age of respondents is likely to be an explanatory variable that affects their parking choices. Respondents aged between 20 and 29 account for the majority (88.6%). The second-largest age group is between 30 and 39, which account for 9%. The other two age groups are between 16 and 19 (3%), and between 50 and 59 (1.5%). The frequency distribution is shown in Figure 9. The concentration on age group between 20 and 29 is a result of the target respondents, which are undergraduate and graduate students at the surveyed universities. The other age groups include younger undergraduate students and faculty members. For model estimation, respondents’ ages are categorized into two groups, young drivers (age 16-29) and older drivers (age 30-79), and the dummy values for them are set to 1 and 0, respectively. Similar to gender, age dummy variable can also be tested in various forms in the utility functions, and the most fitted one can be adopted.
The respondents provide their frequency of parking activities in city centres in the survey. This variable is considered to be significant to their choices as drivers with more on-street parking experience in busy areas may have different parking strategies from drivers who rarely perform parking activities. Although 66 of the 67 respondents hold driver licenses, most of them are students, and their daily commutes are transit, cycling and walking. As a result, from the survey data, the majority of the respondents fall into the first two groups, never performed parking activities and park less than once per month, and they account for 40.3% and 32.8%, respectively. Then the other two frequency groups, one to four times a month and one to four times a week, make up the minority of the respondents, and they constitute 10.4% and 14.9% of the sample size, respectively. Lastly, only one respondent (1.5%) performs on-street parking activities more than five times a week. The latter three groups mainly comprise some of the graduate students and most of the faculty respondents at the two universities. Parking frequency can be classified into two or three groups and introduced in the model as one or two dummy variables, respectively.
4.2.2 Parking Alternative Frequency Analysis

The frequency of the four alternatives chosen by respondents in the parking game is extracted from the dataset and evaluated for different variable groups. The four valid alternatives in the game can be reviewed in previous survey design section 3.1.1.2. The chosen parking alternative from each observation is recorded, and the frequency of each alternative across all the observations are organized according to parking assistance levels, parking game scenarios, and gender of respondents. For illegal parking analysis, frequency of the number of illegal parking activities by the individual is revealed and evaluated for the two gaming levels. The frequency analysis describes various groups of respondents’ parking preferences among the four alternatives in different circumstances.

In order to verify the assumption that the majority of the respondents choose parking spots in a half diamond-shape region that is close to origins in each alternative region, all the streets in the four alternatives are labelled and recorded. From the collected data for assisted parking scenarios, 94.74% (756 out of 798) of the parking choices fall into the specified region. Therefore, the data result proves the validity of the assumption that’s used for walking and driving time calculation in section 3.2.2.
4.2.2.1 Parking Alternative Frequency by Parking Assistance Levels

The frequency of each alternative chosen in each of the two gaming assistance levels (Figure 11), assisted parking and conventional parking, is analyzed. The number of valid observations for the two gaming levels is different, so the frequency is shown in percentage for comparison. According to the chart, it is clear that the frequencies of each alternative for the two gaming assistance levels are similar, with approximately 65%, 10%, 23% and 1.5% of all observations choosing alternative one, two, three, and four, respectively.

For legal parking choices, the frequency of alternative one (inner region) is almost three times the frequency of alternative three (outer region). A similar pattern can be seen for illegal parking choices, alternative two’s (inner region) frequency is much higher than alternative four’s (outer region) frequency. It shows that respondents have alternative preferences, although the attribute levels for parking alternatives in different regions appear an equal number of times according to the attribute level balance property. Therefore, the pattern suggests that the respondents have parking location preferences while they are making their parking choices, and they tend to choose parking spots that are closer to their destinations.

In comparison between legal parking alternatives (1 and 3) and illegal parking alternatives (2 and 4), respondents select legal parking most of the time. Legal parking choice composes 89% of all game plays, while illegal parking choice only accounts for 11%. The reason may be that the expected parking cost of illegal parking spots are always higher than legal parking cost, and the least cost alternatives (legal parking) are favoured.

Moreover, frequencies of illegal parking in conventional parking (11.6%) is slightly higher than that in assisted parking (11%). The higher illegal parking frequency in conventional parking may be caused by running out of time after cruising around the destination to gather parking information and find desirable legal parking spots. On the other hand, respondents are able to quickly locate preferred legal parking spots in assisted parking in which parking information is provided. For the same reason, the frequency of legal parking observations is slightly higher in assisted parking level.
4.2.2.2 Parking Alternative Frequency by Game Scenario

The frequency of each alternative chosen in each of the 12 game scenarios (designed in section 3.1.1.5) for each parking assistance level is evaluated according to the specific combinations of attribute levels. In each gaming level and scenario, the frequency (in percentage) of choosing each alternative is shown in Table 5, and it also presents the values for the four attributes, occupancy level and parking cost for legal parking, and fine and citation probability for illegal parking. The table is labelled and then analyzed by parking assistance level and scenario.
Table 5. Parking alternative frequency for each scenario by parking assistance level

<table>
<thead>
<tr>
<th>Round</th>
<th>Assisted Parking (alternative)</th>
<th>Conventional Parking (Alternative)</th>
<th>Inner Legal</th>
<th>Inner Illegal</th>
<th>Outer Legal</th>
<th>Outer Illegal</th>
<th>Time Frame [min]</th>
<th>Occupancy Level [%]</th>
<th>Parking Cost [$]</th>
<th>Citation Probability [%]</th>
<th>Outer Legal</th>
<th>Parking Cost [$]</th>
<th>Citation Probability [%]</th>
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<tbody>
<tr>
<td>1</td>
<td>0.20 0.03 0.65 0.12</td>
<td>0.51 0.03 0.42 0.05</td>
<td>15</td>
<td>80</td>
<td>5</td>
<td>100</td>
<td>0.40</td>
<td>95</td>
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<td>40</td>
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<td>4</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>0.94 0.03 0.03 0.00</td>
<td>0.75 0.06 0.18 0.00</td>
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<td>95</td>
<td>4</td>
<td>100</td>
<td>0.40</td>
<td>95</td>
<td>4</td>
<td>40</td>
<td>80</td>
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<tr>
<td>3</td>
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<td>100</td>
<td>0.40</td>
<td>80</td>
<td>4</td>
<td>100</td>
<td>40</td>
<td>4</td>
<td>100</td>
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<td>4</td>
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<td>40</td>
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<td>80</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>0.82 0.10 0.07 0.00</td>
<td>0.60 0.18 0.22 0.00</td>
<td>10</td>
<td>95</td>
<td>5</td>
<td>100</td>
<td>0.40</td>
<td>80</td>
<td>5</td>
<td>40</td>
<td>40</td>
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<td>0.77 0.14 0.09 0.00</td>
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<td>0.40</td>
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<td>4</td>
<td>100</td>
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<tr>
<td>7</td>
<td>0.83 0.05 0.12 0.00</td>
<td>0.74 0.03 0.22 0.02</td>
<td>15</td>
<td>95</td>
<td>2</td>
<td>40</td>
<td>0.40</td>
<td>95</td>
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<td>0.69 0.18 0.09 0.04</td>
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<td>9</td>
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<td>0.91 0.00 0.06 0.03</td>
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<td>95</td>
<td>4</td>
<td>40</td>
<td>0.80</td>
<td>80</td>
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<tr>
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<td>0.82 0.13 0.03 0.01</td>
<td>15</td>
<td>80</td>
<td>2</td>
<td>100</td>
<td>0.20</td>
<td>80</td>
<td>5</td>
<td>100</td>
<td>40</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>11</td>
<td>0.51 0.39 0.09 0.01</td>
<td>0.49 0.42 0.07 0.01</td>
<td>10</td>
<td>95</td>
<td>5</td>
<td>40</td>
<td>0.20</td>
<td>95</td>
<td>5</td>
<td>100</td>
<td>20</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>12</td>
<td>0.96 0.01 0.00 0.03</td>
<td>0.97 0.00 0.03 0.00</td>
<td>10</td>
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<td>4</td>
<td>100</td>
<td>0.80</td>
<td>95</td>
<td>10</td>
<td>100</td>
<td>40</td>
<td>4</td>
<td>100</td>
</tr>
</tbody>
</table>

- : favoured legal parking alternative in each scenario
- : lower legal parking cost in each scenario
- : favoured illegal parking alternative in each scenario
- : lower illegal fine in each scenario (& the least possible value)
- : lower illegal occupancy level in each scenario
- : lower illegal citation probability in each scenario (& the least possible value)

Note: inner region alternatives are highlighted if attributes have the same value
First, the table is labelled to clearly identify favoured parking alternatives as well as attribute values that result in low (expected) cost, since it is assumed that drivers preferred low parking cost. For legal parking alternatives in each gaming level, the alternative with a higher frequency is highlighted in green. For illegal parking alternatives, the higher frequency ones are highlighted in red. For legal parking attributes, lower values of occupancy level and parking cost are highlighted in red and green, respectively. If the two alternatives have the same attribute value, the attribute values of inner region alternative (alternative one) are highlighted, because it is assumed that respondents favour parking spots that are closer to the destinations. For illegal parking attributes, lower values of fine and citation probability are highlighted in grey and yellow, respectively. Also, the least possible values for the two attributes are labelled in the corresponding colour, and they are $40 for fine and 20% for citation probability.

Based on the favoured alternatives and labelled attributes in the table, the importance level of the attributes can be evaluated. For legal parking alternative frequencies in each of the two gaming levels, the favoured choice patterns are the same for two gaming levels except for scenario one, and the pattern fits the lower parking cost labelling. However, there is no apparent connection between legal parking choice patterns and lower occupancy level highlights. Therefore, the legal parking alternatives are mainly dominated by parking cost, and closer parking spots are favoured if the parking rates are the same. This conclusion is more evident for assisted parking than conventional parking because alternatives with lower parking cost have higher frequencies than the other alternative in assisted parking across all scenarios. Moreover, the frequencies for alternatives with lower parking cost in assisted parking are all higher than those in conventional parking except for scenario 12 with one percent difference. The phenomenon is reasonable because respondents can easily and quickly locate legal parking spots with lower parking cost in assisted parking, where all parking information is available to them.

For illegal parking alternative frequencies in the two gaming levels, the preference patterns are similar, too. The attributes that dominate driver’s illegal parking choices can be analyzed, and their significance levels can be listed in order. Specifically, scenario two shows that citation probability is more significant than fine because more respondents choose lower citation probability (alternative two) instead of lower fine (alternative four). Citation
probability is also more concerned by respondent than parking spot location since a higher proportion of them select lower citation probability (alternative four) instead of locations that are closer to destinations (alternative two) in scenario nine and twelve. The influence of citation probability on illegal parking choice can also be seen in scenario one, six, and ten. Similar to legal parking choices, scenario five reveals that respondents favour closer illegal parking spots more than those with lower fines. Scenario eight also suggests that closer illegal parking spots are favoured than farther ones with all other attributes stay the same. Lastly, scenario one, seven and eleven shows that fine level affects illegal parking choice as well. In summary, the attributes that have influences on the respondents’ illegal parking choices in descending order are citation probability, location relative to destination and fine level. Furthermore, the frequencies of parking alternatives with the lowest level of both citation probability and fine level are higher in assisted parking than in conventional parking. Again, this is caused by full knowledge of parking spot information in assisted parking, so illegal parking with lower attribute levels can be located quickly.

For comparison between legal and illegal parking choice frequencies in each of the two gaming levels, it is evident that legal parking alternatives are preferred in all scenarios with much higher frequency than illegal parking alternatives, because the parking cost for legal parking is always less than the expected cost of illegal parking. Nevertheless, the difference between the frequencies of preferred legal alternative and preferred illegal alternative is minimal in scenario eleven, as the difference between their expected cost is the smallest among all game scenarios. In scenario eleven, illegal alternative two has the lowest possible expected cost, while the parking cost for legal parking is not the lowest. Thus, it can be concluded that the proportions of legal and illegal parking choices in each game scenario are affected by the difference between their expected cost, with more people choosing legal parking when the difference is significant and conversely when the difference is minimal.

4.2.2.3 Parking Alternative Frequency for Each Gender by Parking Assistance Level

Respondents of different gender identities may have different parking strategies and preferences across the four alternatives. Figure 12 shows the parking alternative frequencies
for different genders in the two gaming levels. For instance, approximately 65% of all parking activities done by women choose alternative one in conventional parking. In general, males and females’ frequency distributions of the four alternatives for both gaming levels are similar. The majority of the respondents favour legal parking alternatives, and they also prefer inner-region alternatives (alternative 1 and 3) in legal and illegal groups. Consequently, the distribution for each gender is similar to the frequency distribution for all respondents in section 4.2.2.1.

For legal parking choice frequencies of males and females, the differences between them are not significant, and there is no clear pattern of parking preferences across alternatives or parking types. However, males have higher frequencies of choosing illegal parking spots than females. For both gaming levels, the frequencies of men choosing alternative one and three are always higher than women’s. This observation indicates that men are more willing to take the risk of being ticketed for illegal parking than women under the two parking circumstances. The conclusion is reasonable, since males are reported to be riskier driver than females in terms of driving behaviours (Rhodes & Pivik, 2011), and thus higher percentage of men may be risk-takers when they are selecting parking spots. The illegal parking frequencies of different genders are similar to the overall trending discussed in section 4.2.2.1, too. The frequencies of choosing illegal parking alternatives in assisted parking level for both genders are found to be lower than those in conventional parking, except for alternative four’s frequency by women.
Figure 12. Parking alternative frequency by gender for two parking assistance levels

(a) conventional parking

(b) assisted parking
4.2.2.4 Illegal Parking Activity Frequency by Parking Assistance Level

In the above section, the illegal parking frequency patterns across different parking assistance levels, game scenarios and genders are found to be more evident than legal parking activities. Consequently, illegal parking choices are further investigated. In Figure 13, the wide blue columns show the number of respondents who choose at least one illegal parking spot in each of the two parking levels, and the smaller columns inside the wide ones indicate the frequencies of the number of illegal parking activities per individual.

As shown in Figure 13, the total number of illegal parkers in assisted and conventional parking levels are 30 and 44, respectively. There may be two reasons for fewer respondents choosing to park illegally in assisted parking. First, assisted parking provides all parking information to drivers, and they are able to locate preferred legal parking spots within the time windows. While the respondents may choose illegal parking after spending time searching for legal parking and running out of time. Second, some people might be fined in conventional parking scenarios first, and they decided not to park illegally to avoid tickets later in assisted parking scenarios. In order to avoid the second potential cause, the order of the two parking levels could be reversed and then check whether the data have the same pattern. Despite fewer illegally parked respondents in assisted parking than that in conventional parking, the number of total illegal parking activities are similar. As compared to illegal parkers in conventional parking, illegal parkers in assisted parking are less by about 32%, while the number of illegal parking activities is only less by 4.3%, meaning individual illegalarker in assisted parking chooses to park illegally more times than individuals in the other parking assistance level. This finding can be visualized by the smaller columns.

The smaller columns reveal the frequencies of the different number of illegal parking activities performed by individuals among the illegally parked drivers in each parking level, and the shapes of the distributions for the two parking levels are slightly different. For conventional parking, the frequency distribution is more skewed right than that in assisted parking, with the majority (45%) of the illegal parkers only select illegal spots once across the twelve scenarios. On the other hand, 27% and 23% of the illegal parkers in assisted parking selected illegal parking spots two and three times, respectively, constituting the majority in assisted parking. The majority in conventional parking level park illegally fewer
times because most drivers choose illegal parking if they accidentally find low-risk illegal parking spots or encounter high parking cost for legal parking spots. On the contrary, most illegal parkers in assisted parking strategically search for low-risk illegal parking spots in every scenario since they are provided with all parking information and sufficient time. As a result, more illegal parked drivers choose illegal parking spots more than once and up to eight times in assisted parking level.

Figure 13. Number of illegal parker and illegal parking activity frequency for two parking assistance levels

4.3 Conclusion

iCity Park survey was successfully conducted at University of Toronto and OCAD University, and 68 sets of data were collected from undergraduate and graduate students, and faculty members. First, univariate analysis of the respondents’ gender, age and their parking activity frequency in busy areas is performed. Then the frequency of each parking alternative in the simulation game is processed by game parking assistance level, game scenario, and gender. Lastly, illegal parking activity is focused on, and the frequency of illegal parking by
individual respondents are analyzed. The findings observed from the data and frequency analysis describe respondents’ parking strategies and preferences, and provide some basis for the magnitude and sign of specific constant values and parameters in the estimated models.
Chapter 5 Model Results and Discussions

5.1 Estimated Models

This section presents the final model results for the three proposed model structures for two parking assistance levels. Biogeme modelling software is used to develop the models using the data collected from iCity Park survey. The MNL models are first estimated based on random utility theory (RUT) and the assumptions for the random components. MNL represents drivers make parking choices directly among four available alternatives. Similar to MNL models, NL models assume drivers’ parking choices in a hierarchical order, which simulates that drivers select one of many nests of parking spots that are correlated, and then make parking choices in that nest. Lastly, MXL models that account for unobserved heterogeneity across individuals are developed. The variables included in the utility functions are modified according to their statistical performance, and some socio-economic variables are involved in some of the models.

5.1.1 Model Specifications

The processed data are used to fit three proposed model structures (MNL, NL and MXL) for conventional and assisted parking levels, resulting in six models in total. Two selection methods used for explanatory variables include forward selection and backward elimination, and forward selection was selected. Appendix A shows the modelling results during forward selection testing for MNL model variable selection for the two parking assistance levels. The estimated final model results for conventional parking are shown in Table 6. Table 7 shows the model estimation results for assisted parking. The model results include the following characteristics: number of observations, number of estimated parameters, final log-likelihood, (adjusted) rho-squared value, variable name, coefficients of estimated parameters and their t-statistics.

The three conventional parking models are estimated from 793 observations. The final specification of MNL model has 12 estimated parameters, the NL has 13 parameters (one nest lower level scale factor in addition), and the MXL model has 16 parameters (four random error standard deviations in addition). 798 observations are used to estimate the three
assisted parking models, and the estimated parameters for the three models, MNL, NL and MXL, are 9, 10 and 13, respectively.

In the final models, most of the parameters are found to be highly statistically significant (95% confidence interval) with the expected sign. Some variables in the models are not statistically significant at 95% confidence interval (t-statistics less than 1.96 or 1.64 with expected sign), but they are retained because they match the expected signs and those variables are able to provide insights for model structure comparison and respondents’ parking behavioural processes. The three models also measure the goodness of fit by final log-likelihood and adjusted rho-squared values. The final likelihood ranges from -428 to -404 for the three conventional parking models, and ranges from -456 to -402 for the three assisted parking models. For both parking assistance levels, the MNL models have the lowest likelihood, and the MXL models have the highest. The adjusted rho-squared values range from 0.58 to 0.62 for all the models. The MNL models have the lowest values, and MXL models have the highest values. Consequently, the MXL models have the best goodness of fit and the MNL models have the worst performance compared to the others. Furthermore, the rho-squared values are considered high for a relatively small data set, thus they indicate that the estimated models fit the sample data well.
Table 6. Model estimation results for conventional parking

<table>
<thead>
<tr>
<th>Variable</th>
<th>MNL</th>
<th>NL</th>
<th>MXL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observation</td>
<td>793</td>
<td>793</td>
<td>793</td>
</tr>
<tr>
<td>The number of parameter estimated</td>
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<td>13</td>
<td>16</td>
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<tr>
<td>Final log likelihood</td>
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<td>-404.062</td>
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<td>Rho-Square value</td>
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<td>0.603</td>
<td>0.615</td>
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<td>Adjusted Rho-Squared value</td>
<td>0.580</td>
<td>0.591</td>
<td>0.600</td>
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<td>Coefficient</td>
<td>t-stat</td>
<td>Coefficient</td>
<td>t-stat</td>
</tr>
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<td>Alternative specific constants</td>
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<td></td>
</tr>
<tr>
<td>Inner legal parking (1)</td>
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<td>0.0 (fixed)</td>
<td>0.0 (fixed)</td>
</tr>
<tr>
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<tr>
<td>Outer legal parking (3)</td>
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<td>0.0 (fixed)</td>
<td>0.0 (fixed)</td>
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<td>Driving time divided by walking time</td>
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<tr>
<td>Legal parking cost</td>
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<td>-12.91</td>
<td>-0.273</td>
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<td>Illegal citation probability</td>
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<td>Illegal citation probability multiplied by a dummy variable for if age is greater than 30</td>
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<td>Lower Level Scale factor of expected maximum utility of nests</td>
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63
Table 7. Model estimation results for assisted parking

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<th>NL</th>
<th>MXL</th>
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<td>The number of parameter estimated</td>
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<td>10</td>
<td>13</td>
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<tr>
<td>Final log likelihood</td>
<td>-256.112</td>
<td>-425.744</td>
<td>-402.407</td>
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<td>Rho-Square value</td>
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<td>Final log likelihood</td>
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<td>0.0 (fixed)</td>
<td>0.0 (fixed)</td>
</tr>
<tr>
<td>Inner illegal parking (2)</td>
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<td>2.390</td>
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<tr>
<td>Outer legal parking (3)</td>
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<tr>
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<tr>
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<td>Lower Level Scale factor of expected maximum utility of nests</td>
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<td>Legal parking nest</td>
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<td>Std. dev. of error components</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Outer illegal parking (4)</td>
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<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

5.1.2 Final Nested Logit Model Structure

Two types of NL model structures are proposed for testing in section 3.3.2.2, and additional nesting structures with only one of the two nests in each proposed structures are tested. The first nesting structure groups the alternatives by inner and outer region as the upper level and has legal and illegal parking in the lower level. The other NL model structure assumes respondent choose legal or illegal parking first (upper level), and then make decisions between inner and outer region (lower level). To validate the two structures, models with only ASCs are estimated for both parking levels, and the criteria to be considered as valid NL structures are that the lower level scale factors should be larger than one with t-statistics higher than 1.64. It is found that the nested structure concerning parking types (legal and illegal parking as upper level) is valid, and the other one does not meet the criteria. However, one of the lower level scale factor for illegal parking nest is not statistically significant,
meaning the illegal nesting structure is not justified. Therefore, the final estimated NL models only contain the legal parking nest, and each of the two illegal parking alternatives is treated as one nest in the upper level.

5.1.3 Final Model Utility Functions

The included variables in the final model utility functions are different from the proposed utility functions in the previous section. Some variables are removed because they are found to be statistically insignificant during the modelling process, and some are modified for better model fit. Moreover, some demographic attributes of respondents are added.

Legal parking occupancy rate and illegal parking fine are found to be less concerned by respondents when they make their parking decisions. For legal parking, respondents would park on the streets as long as there is at least one available parking spot, and the total number of parking spots on the streets does not affect their parking choices. For illegal parking, the fine is found to be less influential in respondents’ illegal parking decisions, although the fine affects the expected cost.

Furthermore, driving time and walking time are combined as one variable by dividing the driving time by walking time. There are slight correlations between driving and walking times since the sum of driving and walking distances are approximately the same in all observations. The similar distance is the distance between initial locations and destinations because the respondents usually choose parking spots between the two points in both parking levels. The new variable represents a ratio of driving portion to walking portion on the way to destinations. The higher the ratio, the closer the parking spot to destinations, since parking spots nearby detonations required relatively long driving time and short walking time. Conversely, a small ratio value indicates that the parking spot is far away from destinations.

Lastly, the influences of respondent’s gender and age on their parking choices are found to be significant. The two demographic attributes are interacted with parking cost and citation probability because the two generic variables’ statistics are resistant to errors in the results. Also, the variable interactions can provide insights on how respondents with different attributes evaluate the alternatives. In the final models, only conventional parking models
include the interacted demographic attributes, which are interactions between parking cost and age, citation probability and age, citation probability and gender. As for respondents’ on-street parking activity frequency, which is also proposed for model testing, it is not included in the final models because it is found to be statistically insignificant.

In summary, the variables in the proposed utility functions are modified according to their statistical performance, and the final utility functions include ASCs, time limit as an ASV, ratio of driving time to walking time, legal parking cost, and illegal parking citation probability for all six models. Additionally, the three conventional parking models have three more demographic variables that are interacted with parking cost and citation probability. Moreover, one lower-level scale factor of illegal parking is estimated for NL models, and four random error components’ standard deviations are presented in the MNL model specifications.

5.2 Discussion

This section analyzes model structures by evaluating their structure variables, such as the nest scale factors in NL models and random error statistics in MXL models. Then the models are compared to each other in terms of goodness of fit, and the implications for respondents’ parking behavioural processes. Then model structure with the best goodness of fit is focused on to compare the estimated coefficients in corresponding models for the two parking assistance levels. The sign and magnitude of the estimated parameters are analyzed, and their indications of respondents’ perception of different variables’ significance in different parking levels are discussed.

5.2.1 Comparison between MNL and NL Models

NL models are proven to capture driver’s hierarchical parking choice processes because the nested structure is justified by the lower level scale factors (5.68 in assisted parking model and 2.22 in conventional parking model for legal parking alternative nests), which are higher than one with t-statistics higher than 1.64. In terms of models’ goodness of fit, NL models are improvements over MNL models. The adjusted rho-squared values of NL models (0.591 for conventional parking model and 0.605 for assisted parking model) are higher than the
ones of MNL models (0.580 for conventional parking model and 0.578 for assisted parking model), indicating there are smaller differences between the observed data and the estimated NL models as compared to MNL models. The models’ final log-likelihood values also show that NL models outperform MNL models since the values are higher in NL models. Therefore, the estimated NL models are proven to be more appropriate than MNL models in terms of estimating driver’s parking choices due to more appropriate model structures. The NL model structure considers correlations among the parking alternatives and partitions them in nests, which partially relaxes the assumption of IID and IIA property of MNL model. In this case, the nested structure correctly predicts that drivers would select the legal parking nest or one of the illegal parking alternatives, and then make decisions regarding parking locations within the legal parking nest if it is selected.

One concern about the findings of the estimated scale factors during the two-nest modelling is that the sample data are downward biased under the nested structure, especially for the conventional parking data. The normal t-statistic assumes homoscedastic errors, meaning there are uniform variances across the independent variables; while the robust t-statistic assumes heteroscedastic errors, which account for random variances. During the modelling process, the robust t value is higher than the normal t value of the lower level scale factor for illegal parking nest in conventional NL model. With the robust t values being larger than the normal t value, it indicates uniform variance in the middle of the data and large random variance at both ends (downward biased). This could be caused by correlations of parking choices to unobserved effects. Consequently, the scale factor for legal parking nest is fixed to result in better models.

5.2.2 Comparison between MNL and MXL Models

The estimated MXL models adequately account for panel effects in the dataset, which are caused by multiple observations form the same individual, because most of the random error components’ standard deviations are statistically significant. The random errors with a general distribution in the MXL models handle panel effects in a general approach and avoid MNL model’s unrealistic assumptions, such as the IID assumption for the random component in utility functions. Therefore, MXL models are able to accommodate the presence of preference heterogeneity for parking choices in the sampled population, and the
method improves the accuracy of estimated models. Consequently, the estimated MXL models have the highest adjusted rho-squared values (0.6 for conventional parking model and 0.623 for assisted parking model) among the three types of models, indicating that the MXL models fit the observed data better than MNL or NL models. The same conclusions can be drawn from the comparison of the final likelihood values. Therefore, the bias of respondents’ individual parking preferences is significant in affecting their parking choices, while MXL models are able to account for the panel effects and outperforms the other two types of models.

5.2.3 Comparison of the Best Fitted Model between Two Parking Assistance Levels

This section analyzes and discusses the implications of the explanatory variables’ sign and magnitude in the MXL models, and they are compared between the two parking assistance levels to reveal respondents’ different parking strategies across the two levels.

Regarding ASCs in the MXL models, all of them are statistically significant. Both models have higher ASC values for inner region alternatives than outer region alternatives, which indicates that respondents prefer parking spots that are close to destinations.

The estimated parking time limit parameters’ signs are intuitive, with a negative sign for inner-region illegal parking, and a positive sign for outer-region parking alternatives. For example, in scenarios with long parking time limits, outer-region alternatives become more practical because respondents are less likely to be late if they park in the outer region as compared to scenarios with shorter time limits. Thus, the utility of outer-region alternatives grows for longer time limits and the parameters should be positive. As shown in Figure 14 and 15, the shares of outer-region parking alternatives increase as parking time limit increases. Conversely, the inner-region alternative two becomes relatively less competitive than alternatives 3 and 4 in terms of relative distance to destination if the time limit is longer, and thus the parameter has a negative sign. The negative sign for alternative two also indicates that respondents always prefer legal parking over illegal parking in the inner region if only time limit is concerned. For the parameter’s magnitudes in the two parking assistance levels, outer region alternatives are compared. In conventional parking, the magnitude of
time limit parameter for alternative 4 (0.198) is larger than alternative 3 (0.070), meaning respondents gains higher utility in outer illegal parking than outer legal parking when the time limit is longer. However, the magnitude relationship between the two alternatives’ parameters are opposite in assisted parking, showing that increase in the utility value of outer legal parking is higher than that of outer illegal parking if the parking time limit becomes longer. A reasonable explanation is that the respondents develop different parking choice habits in the two parking levels. In conventional parking under short time limits, respondents may be more likely to choose illegal parking spots in order to be on time while they are running out of time searching for desired legal parking spots. Although time limit becomes longer in some scenarios, respondents may be stuck in the same situation where there is not enough time as they spend longer time gathering parking information in the network. On the other hand, the time pressure in assisted parking is much lower than in conventional parking, and respondents have sufficient time to compare parking alternatives and select the ones with relatively low expected cost, which are always legal parking spots. Thus, if the time limit is longer in assisted parking, which allows outer-region alternatives to become feasible options, legal alternative gains higher utility than illegal parking due to lower expected cost, as shown by the higher percentage change in the outer-region legal parking alternative’s share than the percentage change in the outer illegal alternative’s share in Figure 14. Figure 15 shows the opposite alternative-share change relationship in conventional parking, which is consistent with the findings above.
Figure 14. Change in outer-region parking alternative share due to change of parking time limit variable in assisted parking

Figure 15. Change in outer-region parking alternative share due to change of parking time limit variable in conventional parking
The ratio of driving time to walking time is introduced into the models to measure respondents’ preference of relative distance between parking spots and destinations. The parameters in both MXL models have a positive sign, which means that drivers gain utility with higher ratio values (longer driving time and shorter walking time). Thus, the positive sign indicates that nearby parking spots around destinations are preferred. The magnitude of the parameter is larger in assisted parking than in conventional parking, and it might be caused by different parking searching scheme in the two parking levels. In conventional parking, respondents would stop approaching destinations once they meet desired parking spots on their way to destinations, which are relatively close to destinations as compared to already explored spots, but not necessarily the closest in the whole network. However, respondents are able to select the closest desired alternatives among all available alternatives in assisted parking, since all parking information is available. Therefore, the parameter magnitude is larger in assisted parking because the selected parking alternatives in assisted parking on average is relatively closer than those selected in conventional parking.

The parameters for legal parking cost are expected to have negative signs because most drivers prefer low parking cost. The magnitude of the parameter in assisted parking (-0.624) is higher than the parameter in conventional parking (-0.563), which suggests that drivers are more sensitive to legal parking cost increases during parking decision makings when they are in assisted parking. As illustrated in Figure 16, the percentage drop in the share of inner legal parking in assisted parking is much higher than that in conventional parking with higher parking cost for the inner legal parking. The availability of parking information is critical in terms of respondents’ perceptions toward legal parking cost. In conventional parking, respondents try to gather parking information while they are cruising, and their goals are to find parking spots with the lowest parking cost if they only prefer legal parking spots. They may select spots with the lowest parking costs from their viewed spots in the end, or select the closest spots to destination if they are running out of time after long-time cruisings. However, the selected legal parking spots may not necessarily be the lowest in the network. As compared to assisted parking, drivers with full parking information can quickly locate legal parking spots with the lowest parking cost in the network. Consequently, more observations in assisted parking show that the respondents choose the lowest-cost legal parking alternatives than those in conventional parking, resulting in higher sensitivity.
towards legal parking cost captured by the assisted parking model than the conventional parking model.

![Figure 16. Change in inner legal parking share due to change of inner legal parking cost variable](image)

The parameters for illegal parking citation probability have an expected negative sign because people prefer illegal parking spots with low citation probability, which leads to low expected cost. The magnitude of the parameter in assisted parking (-19.7) is higher than that in conventional parking (-13.3). In assisted parking, respondents can easily compare illegal parking alternatives’ citation probabilities and choose the lower one in most of the illegal parking observations. On the other hand, comparison between illegal parking requires respondents to cruise in the network to gather information, so they usually randomly choose illegal parking that’s not necessarily with lower citation probability. Another reason that the parameter magnitude is lower in conventional parking is that respondents may run out of time searching for parking and simply choose illegal parking that is closest to destinations to arrive there on time. Therefore, the estimated model for conventional parking shows that respondents are less sensitive to citation probability increases as compared to the assisted parking model. As shown in Figure 17, the percentage drop for inner illegal parking alternative share in assisted parking is higher than that in conventional parking with inner illegal parking citation probability increases.
Some demographic factors are tested during the modelling process and included in the final models, such as gender and age. Although parking choice behaviours of respondents with different gender and age groups are similar in assisted parking, they are quite different in conventional parking. In assisted parking, respondents experience lower time pressure since they are provided with all parking information and arrival times for all the spots, which substantially save their searching time. Therefore, most respondents behave similarly and select alternatives with low expected parking costs that also allow them to arrive at destinations on time. On the other hand, respondents have to spend time gathering parking information, which often leads to insufficient remaining time to park at desired alternatives. Therefore, respondents are usually exposed to high time pressure in conventional parking, and the estimated parameters in MXL model indicate that respondents with different demographic attributes react differently to changes of legal parking cost and illegal citation probability. Specifically, respondents aged greater than 30 are found to be relatively less sensitive to legal parking cost increase since the parameter (0.224) is positive, but in a small magnitude. The model also indicates that respondents older than 30 are less affected by illegal citation probability increases since the parameter (7.04) for the interaction between
older age variable and citation probability is also positive. The respondents in the older age group are mainly faculty members at the two universities and have much higher incomes than the younger respondents who are students. It might be the reason that they are less sensitive to (expected) parking cost. For the gender variable, females are shown to be more sensitive to illegal citation probability than males by the negative sign for the female citation probability’s parameter (-4.3). This conclusion is expected because male drivers are riskier drivers than females (Rhodes & Pivik, 2011), and the data analysis shows that males have higher illegal parking frequency than females in section 4.2.2.3.

The estimated standard deviations of the random error terms are aimed to capture respondents’ perception and preference heterogeneity of the alternatives. For alternatives one and three, the values are relatively low, which indicate that respondents’ preferences for the alternatives are homogeneous, and thus, the utilities are mainly dominated by the explanatory variables. Error terms that have relatively large standard deviations, such as alternative two, indicates that the preference heterogeneity for this alternative is significant. As a result, the utility values of alternative two can vary across individuals even though all the explanatory variables have the same values. The random error standard deviation for alternative four is large in assisted parking (3.17), while it is small in conventional parking (0.425). In assisted parking, alternative four is often considered a feasible option to respondents because its information (attributes and arrival times) is directly provided for comparison with the other illegal parking alternative and the low time pressure in assisted parking allows respondents to compare and park there without being late. However, respondents may often consider alternative four as an infeasible alternative since it is farther from the destinations as compared to the other illegal parking alternative, and they are concerned about punctuality issue under the high time pressure in conventional parking. Therefore, most of the respondents in conventional parking prefer not to select alternative four, resulting in relatively homogeneous preference. However, in assisted parking, respondents can choose outer illegal parking alternative as a feasible option to be at destinations on time, and thus their individual preference for the alternative are significant during their decision-making processes.
5.3 Conclusion

This chapter presents the final estimated models for both parking assistance levels, and the models confirm that the remaining variables have effects on the respondents’ parking choices. The model results demonstrate that NL and MXL models deliver significantly better parking choice prediction results than MNL models. The comparison of the best-fitted models, MXL models, between conventional and assisted parking provides evidence for people’s different parking choice behaviours under the two levels of parking information assistance. A further novel finding from the models is that the respondents’ characteristics affect their parking decisions in conventional parking. Overall, the estimated parameters and model factors are intuitive and reasonable according to the data analysis, and the model statistics that measure the goodness of fit show the resulting models have high estimation performance.
Chapter 6 Conclusions

The main objectives of this thesis are to: (1) use a travel simulator as a SP survey, which involves gamification incentives for better data quality, to collect driver’s on-street parking choices in the presence of legal and illegal parking alternatives and parking enforcement; (2) analyze driver’s parking choice processes and their perceptions of various parking attributes by developing and comparing three different types of discrete choice models; and (3) evaluate the effects of parking ITS applications (PGI system) on driver’s parking strategies. A SP preference survey designed as a parking simulation game is designed and conducted to collect respondents’ parking choice preferences across various gaming scenarios in two parking assistance levels, as well as their socio-economic attributes. The estimated logit models (MNL, NL and MXL models) for two assistance levels and their comparisons in this study are expected to contribute a better understanding of people’s parking choice processes and how different factors affect their parking decisions. The major findings of this thesis are summarized as follows:

6.1 Conclusions on iCity Park as a Data Collection Tool for On-street Parking

The collected data from iCity Park survey have demonstrated that it is able to include a range of the most important factors and expose respondents to simulated hypothetical scenarios. Conventional text based SP surveys are not able to involve as many factors as in the simulator, because that would make respondents take a long time to process the given parking information in each scenario and hard to make a realistic parking choice that is consistent with their real life parking behaviour. iCity Park not only includes some conventional variables in parking choice studies, such as driving time, walking time, dwell time, and legal parking rate, but also contains some less widely investigated factors, such as parking time limit, legal parking occupancy level, and illegal parking’s citation probability and fine. Those less widely used variables can be added in the survey without causing survey fatigue because the travel simulator can visualize most of the variables, not just showing their values as text to respondents. For example, the time limit variable can be visualized by the live clock as time goes. The ratio between vacant and occupied parking spots helps
respondents visualize the legal occupancy level, as they do in real life. Also, different levels of the citation probability for illegal parking are reflected by different colours so that respondents can easily “read” the information.

The iCity Park simulation survey is not only useful in testing respondents’ preference for hypothetical parking alternatives across game scenarios but also testing their parking behaviours under different assistance levels. The simulation game is able to collect truly practical parking decisions under the two parking assistance levels. In conventional parking, respondents have to direct their vehicles in the network to gather parking information. Also, in assisted parking, they are provided with all parking information in the same way as their smartphone would do in reality. The two well-simulated parking assistance levels are close to respondents’ experiences in the real world, and thus the estimated models are able to capture the differences of how the variables affect their parking strategies between the two parking assistance levels.

The data quality from iCity Park is considered high because respondents tend to show their realistic parking choice behaviour, and most of the estimated model parameters are rational and sound. Nearly all the respondents claim that their parking strategies used in the simulation game are identical to their parking behaviours in real life. The intuitive and reasonable sign and magnitude of estimated parameters in all models support respondents’ realistic parking behaviour. Nevertheless, it is expected that respondents care less about the parking cost, such as legal parking cost and illegal parking fine, because they do not have to pay the parking cost or fine in the real world. The high data quality leads to consistent model results. The estimated models indicate many interesting parking behaviours and how they are affected by the included variables and parking assistance levels.

The richness of data from the simulation survey allows accurate modelling and some potential future investigations. Besides the collected parking choices, many other decisions that the respondents made during their parking search processes have been recorded, which would be impossible if conducted as a conventional SP survey. The additional data, such as viewed spots by the respondents, corresponding view durations, and cruising routes, is useful in terms of refining the choice set. For example, viewed spots with long durations and spots that are on cruising routes are included in the choice set. The accurate choice sets contribute
to well-estimated models with high performance for predicting respondents’ parking choice behaviours. Furthermore, there are many game scenario timestamps recorded, which may allow for more profound parking behaviour studies across game scenarios, which is further discussed in section 7.3.

6.2 Conclusions on the Estimated Parking Choice Models

Three types of logit models are estimated using data from the two parking assistance levels, and the final models include parking time limit, ratio of driving to walking time, legal parking cost, illegal citation probability, and interacted gender and age variables. The variables that are not statistically significant are removed from the proposed utility functions.

For the proposed model structures, the NL (legal and illegal parking nests) and MXL model structures are proven to be valid and effective in improving model fits by the statistically significant model parameters. The NL models indicate respondents’ hierarchical parking choice behaviours, in which they would select legal parking nest or one of the two illegal parking alternatives, and then make decisions about parking locations if the legal nest is selected, and it is an improvement over MNL model based on its better goodness of fit. MXL models accommodate respondents’ parking preference heterogeneity using panel data, and it has the best goodness of fit among the three model structures. This shows that incorporating respondents’ parking preference heterogeneity can lead to significant improvements in modelling accuracy and explanatory power for parking choice predictions. Specifically, the estimated standard deviations of the random error terms suggest that respondents’ parking preference heterogeneity for legal parking alternatives are minimal in both parking levels. Nonetheless, it is significant for inner illegal spots (alternative 2) with large utility value variations in both parking level models and outer illegal spots (alternative 4) in assisted parking. Therefore, the modelling results show that there are significant differences across drivers’ perceptions of the parking attributes, such as the explanatory variables in the final models.

The MXL models of the two parking assistance levels are compared, and the parameter estimates are concluded. First, increases in parking time limit shift parking preference from the inner region to outer region alternatives. Also, in conventional parking, it is observed that
respondents have a habit of selecting illegal spots due to high time pressure resulted from parking information gathering, and they are more likely to select outer illegal spots than outer legal spots under longer parking time limits. Second, according to the positive parameters for the ratio of driving to walking time, respondents prefer spots that are close to destinations, and respondents are more sensitive to the ratio in assisted parking as a result of available parking information. The parameters for legal parking cost indicate that drivers are more likely to select legal parking spots with relatively low cost if the network’s parking information is provided to them. Moreover, the models show that respondents prefer low citation probability, while people are more likely to park legally if they have the parking information of the network. For demographic variables, the models indicate that people with different demographic attributes value legal parking cost and illegal citation probability differently only in conventional parking and under high time pressure. People aged greater than 30 are less affected by legal parking cost and illegal citation probability increases, and females are more sensitive to illegal citation probability than males.

The estimated models in this thesis contribute toward a more profound understanding of people’s parking processes and behaviours. The NL models confirm that the parking choice process is more likely to be hierarchical, rather than just one selection level in MNL model. The MXL models prove that individuals have their own preferences toward different parking spots with various degrees of variations. The comparison of the MXL model across two parking assistance levels shows that drivers evaluate parking spot attributes differently, and they may have various parking habits under the two different levels of parking-information availability because of the different information gathering and comparison processes. The findings present drivers’ parking behavioural changes from conventional parking where no parking information is provided to parking that is assisted by ITS technologies. With the rapid development of ITS technologies, easy access to real-time information due to the popularity of smartphones, and potential breakthrough in autonomous vehicles, parking policies should also evolve accordingly and advance with the times. The findings of drivers’ parking choice processes and behaviours in this thesis could potentially provide valuable insights for effective parking policymaking.
6.3 Recommendations for Future Work

This section suggests future work that could be done to improve the survey simulation design, statistical modelling of parking decision behaviour and other potential factors that have influences on respondents’ choices in the simulation survey.

Although the initial locations in the parking games are varied from scenario to scenario, the relative distance between the initial and destination locations are the same. It is designed this way to provide identical parking alternatives to respondents in terms of their relative locations to origins and destinations. However, it would be interesting to investigate whether the distance between origins and destinations affect people’s parking choice behaviours. People’s parking choices might be different after travelling a long distance as compared to a shorter journey. Therefore, different locations for origin could be considered in the parking game design. The same thing could be undertaken for the alternative design to study the changes in people’s parking choice behaviours for different alternative layouts in the network. The designed symmetric alternative layout around destinations in iCity Park is efficient in modelling the influential power of factors, while it is usually not the case in real life and the effects of explanatory variables might differ in different layouts.

Some of the parameters estimated in the models are not statistically significant, while they are retained in the final models because it is felt these variables provide significant insights in parking choice process and model comparisons. The low statistical significance of these variables might be caused by the small size of the dataset, and thus it could potentially be improved by increasing the sample size. Other demographic attributes that were tested but found to be statistically insignificant could be tested for their influences on individual’s parking decision, such as on-street parking frequency in busy areas, level of education, and personal income.

Some additional data saved in the database are not fully utilized, such as timestamps of respondents’ every action in one game scenario and completion time for each game scenario. Potential explorations of feedback learning and habituation of parking strategies might be possible with these data. Respondents may learn from the feedbacks to their parking performance, whether they have chosen cheaper legal parking or low-risk illegal parking,
their latter parking strategies may be affected. Moreover, respondents may also develop their parking habits after a few gameplays and chronically select similar alternatives even though the scenarios have differed. For example, if one respondent received tickets for illegal parking with low risk, he or she might learn from the outcomes and choose not to park illegally for the rest of the game scenarios. Therefore, the order of the two parking-assistance levels might affect the estimated parameters that reflect respondents’ perception towards certain variables, and this could be improved by mix the order of two parking assistance levels for different respondents.
References


Appendix A

Model Utility Function Testing Results for MNL Models

Three tables of model testing results are presented here, and each one is separated into two tables to fit on one page. The testing results are shown in three different tables because they have different table headers for different tested explanatory variables. The models are numbered from 1 to 23 for assisted parking MNL models and 24 to 38 for conventional parking MNL models.

Models in the first table are used to test the proposed utility functions, which only include the basic explanatory variables. The second table shows models that are used to test combined driving and walking time variable, and demographic variables. Specifically, gender, age and parking frequency are tested by introducing each one into the models as one or two dummy variables. The models in the last table are testing the interacted demographic variables.

In each of the three tables, the models that are highlighted in green indicate it is a satisfactory model in corresponding tables for the parking assistance level. For example, model 29 is highlighted in green, so it is the most satisfactory model among the models in the second table for conventional parking, and it is used as the basic model for model testing in the next table. Cells that are in red indicate wrong sign for the estimated parameter, and cells in yellow indicate low t-statistics for the parameter.

The column headers’ abbreviations are listed below (postfix numbers indicate alternatives):
ID  Model ID
Assisted  Assistance level (1 for assisted and 0 for conventional parking)
Log LLH  Final log likelihood
ASC  Alternative specific constant
TL  Parking time limit
DT  Driving time
WL  Walking time
PC  Legal parking cost
OR  Legal parking occupancy rate
CT  Illegal parking citation probability
FP  Illegal parking fine
DT/WT  The ratio of driving time to walking time
G  Gender dummy variable (1 for women and 0 for men)
AGEY  Age dummy variable (1 for younger than 20, 0 otherwise)
AGEO  Age dummy variable (1 for older than 30, 0 otherwise)
F/PF  Parking frequency (1 for at least 1-4 times a month)
PCF  PC multiplied by a dummy variable for if gender is female
PCO  PC multiplied by a dummy variable for if age is greater than 30
CTF  CT multiplied by a dummy variable for if gender is female
CTO  CT multiplied by a dummy variable for if age is greater than 30
Table 1:

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