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Parking Survey Design Using Gamification

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Abstract

We present a survey methodology to collect parking behavior data. The survey is a game that exposes respondents to a wide range of hypothetical parking scenarios including information availability (on parking spots) and the possibility of illegal parking. The respondents make parking choices by playing the game. We use incentive mechanisms from the gamification literature to replicate real-world decisions. The survey can overcome choice set deficiencies of conventional methods of revealed and state preference surveys (e.g., unavailable choice sets in revealed preference and large choice sets in stated preference). We record detailed travel decisions throughout the parking process and use the data to develop choice models. The Mixed logit model demonstrates the significance of parking preference heterogeneity. According to the model, respondents are more likely to park legally when they are provided full information about the status of parking spots. Moreover, male respondents are more likely to park illegally.

Keywords: Discrete choice models; mixed logit model; parking, policy; stated preference; gamification; parking simulation

1. Introduction

Parking is a tedious part of auto travel. Drivers in the U.S. spend an average of 17 hours per year searching for a parking spot (USA Today, 2017). In New York, the average search time is 15 minutes per trip, and it costs 33 dollars to park for two hours (INRIX, 2017). Similar statistics are reported in many other major urban cities. Many policies are imposed to alleviate parking burdens. The City of San Francisco initiated a program called SF-Park in 2011 that used sensors in the pavement to collect parking occupancy information (SF Park, 2011). The data were disseminated through an app to help drivers find a spot faster. In another attempt to improve the parking experience, the City of Toronto developed a mobile application called Green-P that allows travelers to pay for parking online on an hourly based price. A preliminary step in the successful implementation of any policy is to collect data to better understand driver parking behavior.

Parking behavior models allow governing agencies to assess a range of policies and technologies. Behavioral models are data driven. Conventional parking data collection methods have limitations that impede their ability to accurately model parking behavior. The first common method is the Revealed Preference (RP) approach that analyzes choices already made by drivers in real-life. This approach often cannot capture the choice-set of the drivers. Precisely, RP data shows which parking spot was chosen, but does not show the spots that a driver considered before making a decision. The second approach is the Stated Preference (SP) survey that exposes drivers to hypothetical scenarios and reports their decisions in different environments. SP surveys commonly have large choice-sets due to a large set of attributes and alternatives. Thus, the surveys are designed in a limited capacity to avoid confusion and fatigue for the respondents and bias in the collected data.

This paper presents an alternative methodology to collect parking data. We present a gamified parking survey that exposes respondents to a wide range of hypothetical scenarios. The respondents make parking choices by playing the game. We use incentive mechanisms from the gamification literature to better replicate real-world situations. The gamified survey collects respondent decisions under scenarios that represent specific policies. The scenarios include parking enforcement, pricing policies, and parking information assistance. We use the collected data to estimate discrete choice models to predict parking behavior using three types of logit models.

Our parking simulation survey overcomes some deficiencies of conventional RP and SP survey methods. Unlike the RP method, we can observe the choice-set of the drivers, because the entire gameplay is recorded. The gamified survey also overcomes the drawbacks of conventional SP surveys, by allowing us to simultaneously vary more than one factor without confusing the respondents. We develop a mixed logit model from the gamified survey and capture versatile insights. As an example, the respondents are more likely to park legally when they are provided full information about the status of parking spots. Moreover, respondents that are 30 years or older or male are more likely to park illegally.

This remainder of this paper is organized as follows. Section 2 reviews the existing literature on parking choice and relevant data collection methods. Section 3 explains the design of the gamified survey and the discrete choice model structures used to analyze the data. Section 4 presents the data from the survey and the model results. Section 5 discusses the model results in terms of model structure and factors that influence parking behavior. Section 6 concludes the study as it discusses the effectiveness of the data collection method, summarizes the key findings, and makes recommendations for future research.

2. Literature Review

Parking data collection methods include RP and SP approaches. Each approach has limitations for model development. Gamified surveys overcome some of the shortcomings of these two methods. In this section, we first discuss conventional parking data collection methods. We then review gamified surveys in various applications with incentive mechanisms. Lastly, we review existing parking choice models and discuss their results.

2.1 *Revealed and stated preference surveys*

Drivers choose on-street parking from a set of vacant spots near their destinations considering factors such as parking cost, distance from destination, and others. Discrete choice models assess the importance of each factor in parking choices. The models require extensive data commonly collected using RP or SP surveys. RP refers to information collected about real-life choices, while SP asks respondents to make a choice in hypothetical scenarios. Several studies use 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 that limit their use.

The challenge for RP surveys of parking is in defining the choice set and obtaining attribute values of non-chosen alternatives. In the parking context, the choice set includes all available parking spots considered by the driver. Capturing the choice set is challenging since it is resource-intensive to obtain the attributes of all parking alternatives, especially occupancy (i.e., the ratio of occupied parking spots over the total number of spots). Consequently, RP surveys usually require the assistance of technology. Axhausen and Polak (1991) showed the difficulty to define the choice set of parking activities with the available technology at the time. Even today, conducting RP surveys for parking with a defined choice set is daunting because it requires GPS data from participants and occupancy data from street cameras or sensors embedded in the on-street parking spots. Cameras and sensors are only available in a limited number of urban areas such as San Francisco and Washington D.C. Nevertheless, many studies have used RP data collection to study parking choice. Ergun (1971), Austin (1973), Gillen (1978), and Van der Goot (1982) developed parking choice logit models and defined the choice set by classifying the parking spots according to their distance from the destination.

Several studies remedy the choice set problem of RP surveys by limiting the scope of the survey. Kelly and Clinch (2009) conducted an RP survey to estimate on-street parking price elasticity and remedied the choice set problem by limiting their test area to a small central region with on-street parking in Dublin. However, the choice set grouping approach according to location has several drawbacks. First, it is challenging to understand the significance of influential factors on parking choice because some factors 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 to other jurisdictions (Axhausen and Polak, 1991).

SP surveys address some shortcomings of RP surveys by defining the choice set for respondents and varying the attribute levels of influential factors under hypothetical scenarios. The scenarios in SP surveys allow for practical and hypothetical alternatives and an extended range of attribute levels for respondents. Therefore, the estimated models are better able to evaluate each attribute's influence. Axhausen and Polak (1991) used disaggregate data collected from an SP survey to model driver sensitivity to changes in parking attributes. Habib et al. (2013) conducted an SP survey to investigate the influence of parking fees at transit stations and mode choice behavior under varying parking fee and occupancy levels.

The choice set for SP surveys could be too large due to abundant attributes and alternatives. 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 an SP survey with five alternatives and 20 factors. They show that the choice set would be too large, making the survey complicated and inefficient. Consequently, the alternatives were limited from five to three and some attributes were only assigned one level by making assumptions about parking choice. To reduce the size of the choice set, Golias et al. (2002) also limited their parameters and reduced the number of attribute levels by making assumptions, such as zero search time for off-street parking. With the limitations of 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 (i.e., number of attributes and attribute levels).

2.2 *Gamified surveys*

Gamified surveys can be used to collect travel behavior data in transportation systems. They overcome some deficiencies of RP and SP surveys. First, they can present the hypothetical scenarios of the SP surveys in a controlled environment. 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 can capture the significance of specific factors compared to RP surveys. For example, repeatedly chosen alternatives in simulators are influenced by the respondent's perception of controlled factors. However, they may be the result of uncontrolled factors that catch the respondent's attention in RP surveys. Lastly, simulators can explore the impact of technologies that may not be feasible to implement in the field, such as parking guidance information (PGI) systems (Koutsopoulos et al., 1995).

Several studies demonstrate the feasibility of gamified survey data collection. Bonsall and Perry (1991) were the first to design an interactive route-based simulator to collect data for identifying factors that influence route choice. Their simulator collected data on routing advice from an advanced traveler information system (ATIS). Bonsall et al. (1997) used a route choice simulator to collect data for estimating route choice under different types of ATIS. Chen and Mahmassani (1993) developed a similar simulator that collected user choices including route departure choice, en-route diversion decisions and route choices. The technology related to parking, such as PGI systems, is still under development, thus only a few studies capture their impact on parking choice using travel simulators.

PARKIT is a travel simulator that collects data to evaluate the impact of technologies such as PGI systems on parking choice (Bonsall and Palmer, 2004). PARKIT is designed for off-street parking only, thus, there is a need for a travel simulator that collects data that captures parking choice behavior for on-street parking. The level of complexity for on-street parking is higher due to the larger dispersion of vacant on-street parking spots, more complex attribute variations and the possibility of illegal parking.

Incentives create motivation for respondents to play the game as they would act in real-life. Wang et al. (2016) classify incentives into three categories: extrinsic (economic), intrinsic (entertainment or game-based), and internalized extrinsic (reputation-based) or social incentives. Wang et al. (2016) consider gamification to be the most effective way of engaging people to conscientiously perform tasks and provide high-quality data. Arakawa and Matsuda (2016) also introduced gamification mechanisms as a substitute for monetary incentives into their participatory urban simulation. They found that the participation rate increased by 20% after they gamified the process. Kashian et al. (2014) designed a mobile application to collect attribute information for "Points of Interest" and confirmed that using gamification as an incentive increased the number of participants. Kazhamiakin et al. (2015) used gamification incentives for voluntary behavioral change and the results indicated a high participation rate. Although gamification incentives are 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 parking data.

2.3 *Parking choice models*

Technological advancements in the past decade have led to the development of PGI systems that integrate traffic monitoring, communication and information processing to provide real-time information on parking. PGI systems have the potential to save parking search time. Surveys conducted in British cities indicate that parking space searching time accounts for up to 25% of the total travel time of trips to central urban areas (Polak and Vythoulkas, 1993) and the proportion could increase 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 urban areas.

Parking policies and their resulting parking patterns impact the transportation system performance. Ramadan and Roorda (2017) used a traffic microsimulation model to quantify the impact of illegal on-street parking in the City of Toronto. Nourinejad and Roorda (2017) found that parking pricing could reduce or induce demand depending on the elasticity of parking dwell time. Danwen (2010) presented a mode choice model that identified the sensitivity of people's travel mode choices and travel demand to changes in the parking fare. Nourinejad et al. (2014) developed a parking choice model and a traffic simulation module to investigate the impact of truck parking policies in city centers.

Several studies use traffic simulation models to model parking search behavior. Thompson and Richardson (1998) presented a model to endogenously determine choice sets and provided a behavioral modeling framework based on experiences of parking searching. Lam et al. (2006) proposed a time-dependent traffic equilibrium model that incorporates traveler departure time, route, and parking-related choices and found several influential factors on parking choice, such as travel demand, parking capacity and pricing. With the same purpose, Leurent and Boujnah (2014) developed a network model to represent driver route and parking choice according to travel demand (origin-destination pair).

Many more studies are oriented towards assessing factors that affect parking choice behavior. Axhausen and Polak (1991) estimated parking models and showed that the model with separate time attributes (travel time, search time and walk time) provided more accurate predictions of parking choice. Hunt and Teply (1993) estimated a nested logit parking model that incorporated attributes other than cost and walking distance, such as the relative location of parking space to destination and origin and parking capacity. Golias et al. (2002) developed a binary logit model to predict parking type choices and found that the critical factors are parking cost, parking search time, dwell time and walking time. Simićević et al. (2013) estimated multinomial logit models, which showed that parking price and dwell time limit affect parking choices. Chaniotakis and Pel (2015) estimated discrete choice models and concluded that parking search time was crucial. Many other studies 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 these studies and the ones discussed above are summarized in Table 1. The checkmarks indicate that the attributes were surveyed and considered in model development.

Table 1. Parking choice model attributes considered in the literature. Black checkmarks indicate that the attributes have a statistically significant influence on drivers' parking choice, and grey checkmarks indicate that their influence on parking choice is negligible.

Study	Cost	Walking Distance	Travel Time	Search Time	Dwell Time	Parking Type	Illegal Fine	Purpose	Occupancy	Vehicle Safety	Age	Income	Sex	PGI System
Gillen (1978)	✓	✓	✓	✓							(✓)	✓	(✓)	
Hunt (1988)	✓	✓	✓	✓		✓								
Axhausen and Polak (1991)	✓	✓	✓	✓		✓	✓	✓			(✓)		(✓)	
Hunt and Teply (1993)	✓	✓	✓	✓		✓				(✓)				
Golias et al. (2002)	✓	✓		✓	✓	✓		(✓)			(✓)	(✓)	(✓)	
Bonsall and Palmer (2004)	✓	✓	✓					(✓)						✓
Van der Waerden (2012)	✓	✓	✓	✓	✓	✓		✓	✓	(✓)	✓	✓		✓
Simićević et al. (2013)	✓				✓	✓		✓	(✓)		(✓)		(✓)	
Chaniotakis and Pel (2015)	✓	✓	✓			✓			✓					

3. Methodology

3.1 *Survey design*

In the gamified survey, we give the respondents several parking scenarios in which they have a parking task to complete. In each scenario, the respondents have to reach an assigned final destination within a given time frame (e.g., they have to park within 10 minutes). The total parking time includes cruising for parking and walking from the spot to the final destination. A penalty is applied if the task is not completed on time. Respondents can choose to park legally and pay a fee or park illegally and receive a fine with a given probability. They make their choice by observing the legal parking fee and the illegal parking fine and citation probability.

Each parking spot is a distance away from the destination, which influences the walking time. Some parking spots are already occupied, and some are vacant. Respondents observe the occupancy status and choose a vacant spot. They are rewarded for completing the task on time and penalized for the costs they incur such as the parking fee or citation fine.

The choice set for each parking task consists of five alternatives. The first two alternatives are the legal and illegal parking spots within a one-block-distance of the destination, located in the red region of Figure 1, called the 'inner region'. The second two alternatives are legal and illegal parking spots that are within a two-block-distance but outside one-block-distance of the destination located in the grey region of Figure 1, called the 'outer region'. The last alternative includes parking spots that are more than two blocks from the destination.

The attributes are the characteristics of parking spots observed in each parking alternative such as parking fee and availability. Attributes of the parking spots on each block face have the same level, although there are small variations across different spots within a block face in driving and walking times. We ignore small variations across spots within a block face.

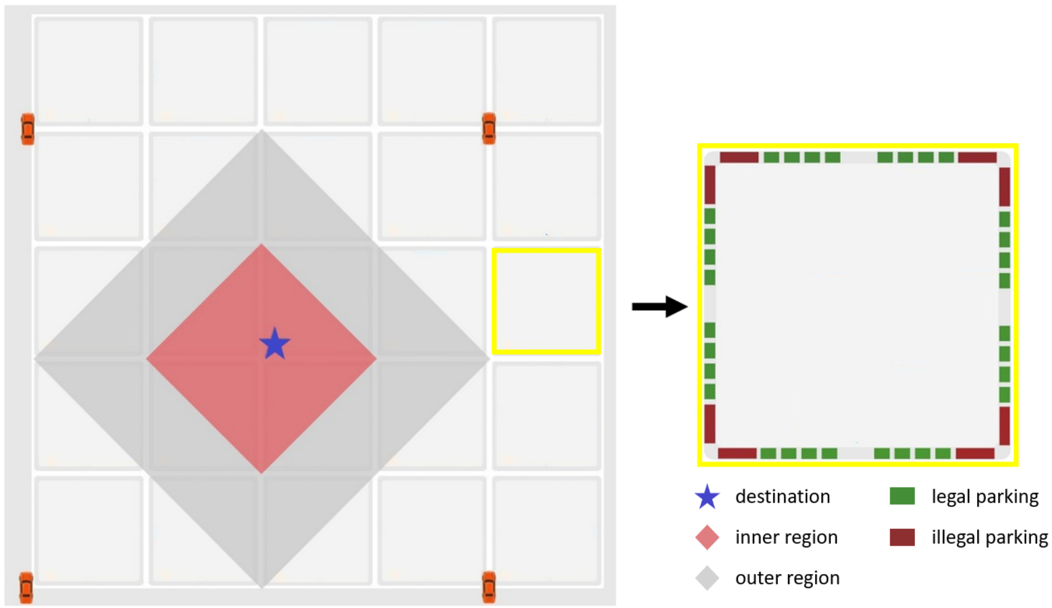

Figure 1. Parking alternative regions.

Each scenario consists of a specific combination of attribute levels. Six attributes characterize the parking alternatives within a scenario: (i) parking dwell time, (ii) parking time frame (allowable time limit to arrive at the destination), (iii) legal parking fee, (iv) occupancy level (number of occupied spots), (v) citation probability per hour, and (vi) illegal parking fine. We select these six attributes because they are found to be statistically significant in the parking choice literature (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 effects of attributes on the parking choice is linear (Golias et al., 2002; Rose & Bliemer, 2009; Molin, 2011; Chaniotakis & Pel, 2015). Each attribute is described below in detail.

We consider two parking assistance levels called conventional and assisted parking. In conventional parking, shown in Figure 2, respondents only observe parking spots around their current location within a limited distance. Parking attributes within a one-block distance from the vehicle's current location can be viewed, and any vacant parking spot can be selected. Drivers cruise around their destination to check available spots using the keyboard arrow keys. Parking alternatives for conventional parking only consist of parking spots observed by the user while cruising.

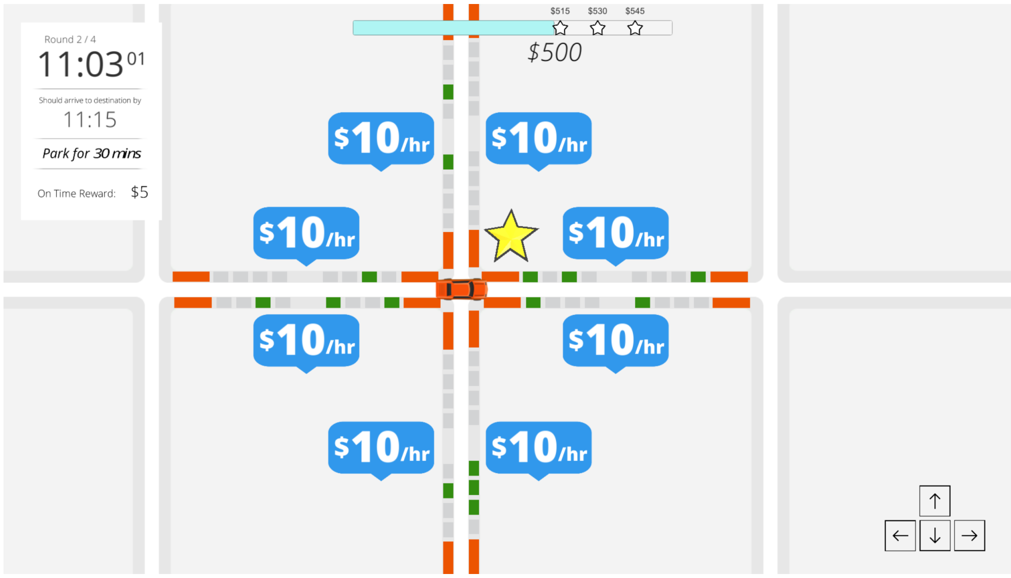

Figure 2. Conventional parking user interface

In assisted parking, the respondents can observe all parking alternatives in the network as shown in Figure 3. Assisted parking intends to simulate parking tasks with the help of PGI systems. Respondents can view the whole network and zoom into blocks to view parking alternatives in detail. Consequently, all attributes of the parking alternatives are known in advance. Respondents choose one spot to park, and the vehicle is directed to the selected spot using the shortest path.

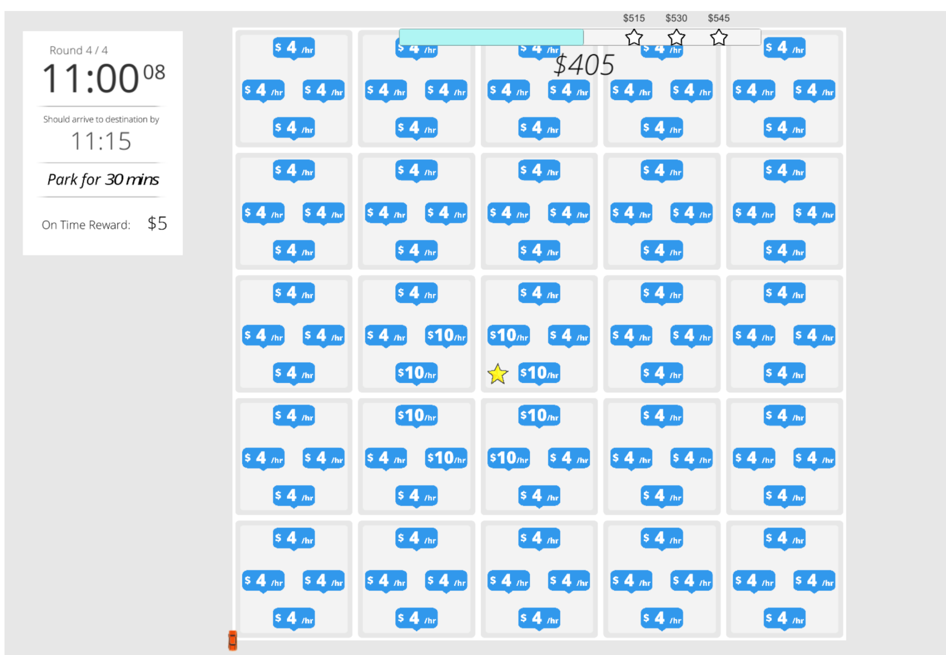

Figure 3. Assisted parking user interface

We generate 12 scenarios using a fractional factorial design. This design is generated using a simultaneous choice set creation method, also called the L^{MN} design method that preserves the orthogonality of the attributes both within and between the alternatives (Molin, 2011). 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 are estimated well over the range of levels and avoids attribute levels with missing data points.

A scoring system is designed to provide feedback to each respondent's parking performance. It works as a gamification incentive that replaces extrinsic (monetary) incentives to motivate respondents to make parking choices as they would in real life. A score bar is placed on the top part of the user interface to show the current score and some target scores as thresholds. The thresholds are shown as stars that can be gained in the game and the number of stars gained reflects users' parking performance granting them a sense of achievement.

The second part of the survey is a questionnaire that collects socio-economic information 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), we select potential variables that may influence driver choices. The variables include age, gender, occupation status and type, education level, household characteristics (i.e., household size, residence type), usual travel mode, parking frequency, parking purpose, relative walking speed and income. The questionnaire consists of 17 multiple-choice questions.

3.2 *Choice model*

We use discrete choice models, based on random utility theory (Ben-Akiva and Lerman 1985) to evaluate the influential factors for on-street parking choices. We use the data collected from the gamified survey to develop three types of parking choice models: multinomial logit (MNL) model, nested logit (NL) model and mixed logit (MXL) model. We describe the alternatives, attributes, and model structures.

Respondents are assumed to gain utility from selecting a parking alternative. The utility function, U, for each alternative consists of systematic, V, and random components, ε. The systematic utility function is a linear-in-parameter function of the attributes, x, and corresponding coefficients, β. The random component explains the unobserved random variations in parking choices. The utility function is:

$$U_i = V_i + \varepsilon_i = (\beta x)_i + \varepsilon_i, \tag{1}$$

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 μ, which defines the dispersion of the probability density function (PDF). Type I distribution is a common 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. A mixed logit (MXL) model is also estimated to account for the heterogeneity among respondents of the perception and preference of parking alternatives. The MXL model is based on the formulation of the MNL model, with random parameters or an additional random error term in the utility functions.

Panel effects exist in the dataset because each respondent performs multiple tasks in the survey, and respondents have different alternative preferences based on unobserved biases. For example, some individuals may be averse to parking illegally, and some may prefer parking alternatives that are close to the destination regardless of the other parking attributes. The unobserved effects that influence parking choices vary across individuals, and the associated bias can affect the accuracy of estimated parking choice models. MXL model structure can be used to deal with such individual preferences.

The 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 combination of logit and probability density functions forms the choice probability. One method of incorporating MXL model is the error components approach that captures the unobserved effects by adding a separate error component in the random component. The utility function has the following form:

$$U_i = V_i + \varepsilon_i = \beta_i x_i + (\eta_i + \varepsilon_i). \tag{2}$$

The utility function adds a random error term, η, with zero mean and a general distribution in addition to the original formulation. The probability density function of η is denoted by $f(\eta|\Omega)$ where Ω are the fixed parameters of the distribution. Since the remaining error term, ε, is still assumed to be IID extreme value distribution over alternatives, the conditional choice probability is logit with a given value of η, defined as:

$$L_i(\eta) = \frac{\exp(\beta_i x_i + \eta_i)}{\sum_{i'=1}^{I} \exp(\beta_i x_{i'} + \eta_{i'})}. \tag{3}$$

The unconditional choice probability is the MNL formulae integrated over all values of η weighted by the density of η :

$$P_i = \int L_i(\eta)\, f(\eta|\Omega) d\eta. \tag{4}$$

The most popular distributions used for random terms are normal, triangular, uniform and lognormal. We select the normal distribution 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 a bounded distribution in terms of anticipating respondent preferences over alternatives, which can be positive or negative (Jiang et al., 2018). Also, Hess et al. (2005, 2006) demonstrated that an MXL model using unbounded distribution (i.e. normal distribution) always has a better fit than the model with bounded distributions. Lastly, many studies estimated MXL models based on data from SP surveys using normal distributions. These models resulted in better fit than other types of distributions (Hess & Polak, 2005; Yáñez et al., 2010; Brownstone et al., 2000; Jiang et al., 2018; Lovreglio et al., 2016). We use Biogeme (Bierlaire, 2019) to estimate the MNL, NL and MXL models using data collected from the gamified survey.

4. Results

We conducted the gamified survey at the University of Toronto and Ontario College of Art and Design (OCAD) University in June 2019. We recruited respondents in faculty computer labs. We also advertised the survey via invitation emails containing an application download link. Survey respondents include undergraduate and graduate students, and faculty members at the two universities. A total of 68 respondents completed the survey with 793 valid observations for conventional parking and 798 observations for assisted parking. Among all the respondents, 40 (59.7%) are male, and 27 (40.3%) are female. The majority of respondents are aged between 20 and 29 (88.6%). The second-largest age group, between 30 and 39, accounts for 9%. The other two age groups are between 16 and 19 (3%), and between 50 and 59 (1.5%).

We used the processed data to fit three proposed model structures (MNL, NL, and MXL) for conventional and assisted parking levels, resulting in six models in total. We used forward selection for explanatory variable selection. Experimentation with nesting structure of the NL model resulted in a final structure that contains one ‘legal parking’ upper-level nest (with inner and outer regions from Figure 1 as alternatives within that nest), and each of the two illegal parking alternatives as upper-level alternatives.

Table 2 presents the estimated final model results for conventional parking, and Table 3 shows the model estimation results for assisted parking. Most of the parameters are found to be 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 can provide insights for model structure comparison and parking behavior. The goodness of fit of the three models is measured by final log-likelihood and adjusted rho-squared values. For both parking assistance levels, the MNL models have the lowest likelihood and adjusted rho-square values, and the MXL models have the highest. Hence, the MXL models can be considered the better performing model structure.

The variables in the final model utility functions are modified from those collected in the gamified survey. Legal parking occupancy rate and illegal parking fine are found to be of less concern to 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.

Driving and walking times are combined as a ratio of the driving time to walking time to the destination. The higher the ratio, the closer the parking spot is to the destination. A small ratio indicates that the parking spot is farther from the destination.

In summary, the final specification was selected based on statistical performance, and the final utility functions include alternative specific constants, time limit as an alternative specific variable, the 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 include demographic variables that are interacted with parking cost and citation probability. 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.

Table 2. Model estimation results for conventional parking

Variable	MNL		NL		MXL	
Number of observations	793		793		793	
The number of parameters estimated	12		13		16	
Final log-likelihood	-428.224		-416.649		-404.062	
Rho-Square value	0.592		0.603		0.615	
Adjusted Rho-Squared value	0.580		0.591		0.600	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Alternative specific constants						
Inner legal parking (1)	0.0 (fixed)	-	0.0 (fixed)	-	0.0 (fixed)	-
Inner illegal parking (2)	2.190	3.04	2.010	2.96	2.810	3.25
Outer legal parking (3)	-2.300	-3.54	-1.320	-3.12	-2.870	-3.89
Outer illegal parking (4)	-3.990	-2.16	-3.600	-2.03	-5.240	-2.46
Parking time limit						
Inner legal parking (1)	0.0 (fixed)	-	0.0 (fixed)	-	0.0 (fixed)	-
Inner illegal parking (2)	-0.226	-3.58	-0.197	-3.45	-0.316	-4.29
Outer legal parking (3)	0.043	0.91	0.030	1.18	0.070	1.34
Outer illegal parking (4)	0.110	0.80	0.096	0.72	0.198	1.31
Driving time divided by walking time	0.390	1.20	0.251	1.30	0.530	1.45
Legal parking cost	-0.473	-12.91	-0.273	-5.24	-0.563	-11.95
Illegal citation probability	-11.500	-8.16	-8.550	-6.72	-13.300	-7.74
Legal parking cost multiplied by a dummy variable for if age is greater than 30	0.204	2.54	0.108	2.34	0.224	2.33
Illegal citation probability multiplied by a dummy variable for if gender is female	-1.790	-2.06	-1.720	-2.04	-4.300	-2.64
Illegal citation probability multiplied by a dummy variable for if age is greater than 30	5.470	3.53	3.410	2.88	7.040	3.20
Lower-Level Scale factor of the expected maximum utility of nests						
Legal parking nest	-	-	2.220	4.87	-	-
Std. dev. of error components						
Inner legal parking (1)	-	-	-	-	-0.283	-0.79
Inner illegal parking (2)	-	-	-	-	1.560	5.34
Outer legal parking (3)	-	-	-	-	-0.920	-4.06
Outer illegal parking (4)	-	-	-	-	-0.452	-0.40

Table 3. Model estimation results for assisted parking

Variable	MNL		NL		MXL	
Number of observations	798		798		798	
The number of parameters estimated	9		10		13	
Final log-likelihood	-456.112		-425.744		-402.407	
Rho-Square value	0.586		0.614		0.635	
Adjusted Rho-Squared value	0.578		0.605		0.623	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Alternative specific constants						
Inner legal parking (1)	0.0 (fixed)	-	0.0 (fixed)	-	0.0 (fixed)	-
Inner illegal parking (2)	2.820	3.85	2.390	3.46	4.170	3.97
Outer legal parking (3)	-4.610	-6.70	-1.050	-2.00	-5.040	-6.48
Outer illegal parking (4)	-4.710	-2.42	-4.700	-2.49	-5.830	-2.45
Parking time limit						
Inner legal parking (1)	0.0 (fixed)	-	0.0 (fixed)	-	0.0 (fixed)	-
Inner illegal parking (2)	-0.228	-3.31	-0.165	-2.85	-0.383	-4.62
Outer legal parking (3)	0.240	5.00	0.055	1.95	0.270	5.09
Outer illegal parking (4)	0.265	1.93	0.263	1.96	0.234	1.57
Driving time divided by walking time	0.436	1.52	0.124	1.17	0.694	1.86
Legal parking cost	-0.533	-15.20	-0.132	-2.10	-0.624	-14.01
Illegal citation probability	-14.800	-9.33	-9.540	-7.17	-19.700	-9.67
Lower-Level Scale factor of the expected maximum utility of nests						
Legal parking nest	-	-	5.680	2.08	-	-
Std. dev. of error components						
Inner legal parking (1)	-	-	-	-	-0.510	-2.50
Inner illegal parking (2)	-	-	-	-	3.000	6.05
Outer legal parking (3)	-	-	-	-	-0.019	-0.07
Outer illegal parking (4)	-	-	-	-	3.170	3.60

5. Discussion

In this section, we analyze the model structures by evaluating factors that are specific to the structures, such as the random error statistics in MXL models. We compare the models in terms of goodness of fit. We then focus on the model structure with the best goodness of fit and compare the estimated coefficients in corresponding models for the two parking assistance levels. We analyze the sign and magnitude of the estimated parameters and their implications for parking behavior.

The estimated MXL models account for significant panel effects in the dataset since most of the random error standard deviations are statistically significant. The random errors with a general distribution in the MXL models handle panel effects and avoid the MNL model's unrealistic assumptions, such as the IID assumption for the random component in utility functions. The estimated MXL models have the highest adjusted rho-squared values among the three types of models. The same conclusions can be drawn from the comparison of the final likelihood values. The bias of respondents' individual parking preferences is significant in affecting their parking choices, and since MXL models can account for the panel effects, it outperforms the other two types of models. The MXL models (for assisted and conventional parking) have higher alternative specific constant values for inner region alternatives than outer region alternatives indicating that, all else being equal, respondents prefer parking alternatives that are closer to destinations.

The estimated parking time limit parameter 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 longer parking time limits, outer-region alternatives become more desirable because respondents are less likely to be late if they park in the outer region. As shown in Figures 5 and 6, the shares of outer-region parking alternatives increase with parking time limit increases. Conversely, the inner-region alternative 2 becomes relatively less competitive if the time limit is longer. The negative sign for the inner-region illegal alternative also indicates that respondents prefer legal over illegal parking in the inner region if only the time limit is concerned.

We compare the parameter's magnitudes of the outer region alternatives in the two parking assistance levels. In conventional parking, the magnitude for the outer-region illegal alternative (0.198) is larger than the outer-region legal alternative (0.070), meaning respondents gain higher utility from illegal parking than legal parking in the outer region when the time limit is longer. However, the relationship between the magnitudes of the two alternatives' parameters are opposite in assisted parking. A reasonable explanation is that the respondents develop different parking choice habits in the two parking assistance levels. In conventional parking under short time limits, respondents may be more likely to choose illegal parking alternatives in order to be on time. In contrast, in assisted parking, respondents have sufficient time to compare and select the alternatives with lower expected cost, which are always legal parking alternatives. Thus, assisted parking affords the extra time to select lower cost legal alternatives over illegal parking alternatives, as shown by the higher percentage change in the outer-region legal parking alternative's share in Figure 5. Figure 6 shows the opposite alternative-share change relationship in conventional parking.

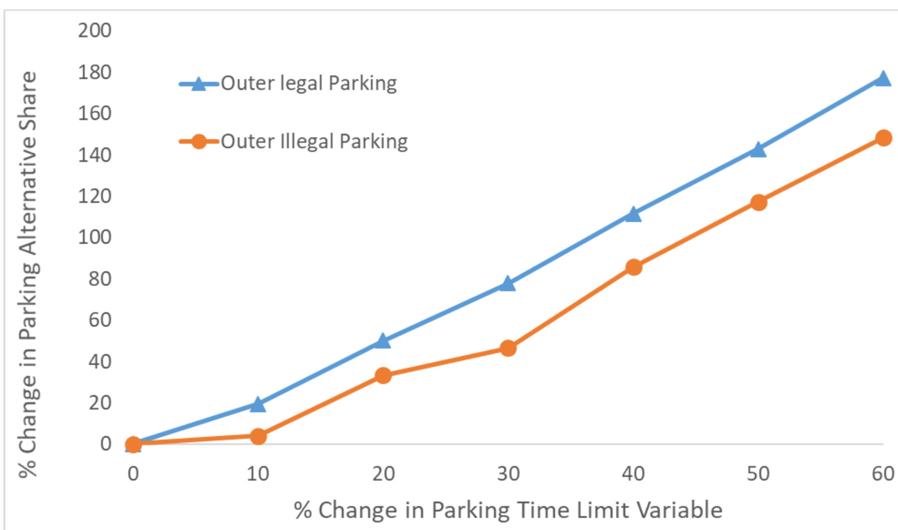

Figure 5. Change in outer-region parking alternative share due to change of parking time limit in assisted parking.

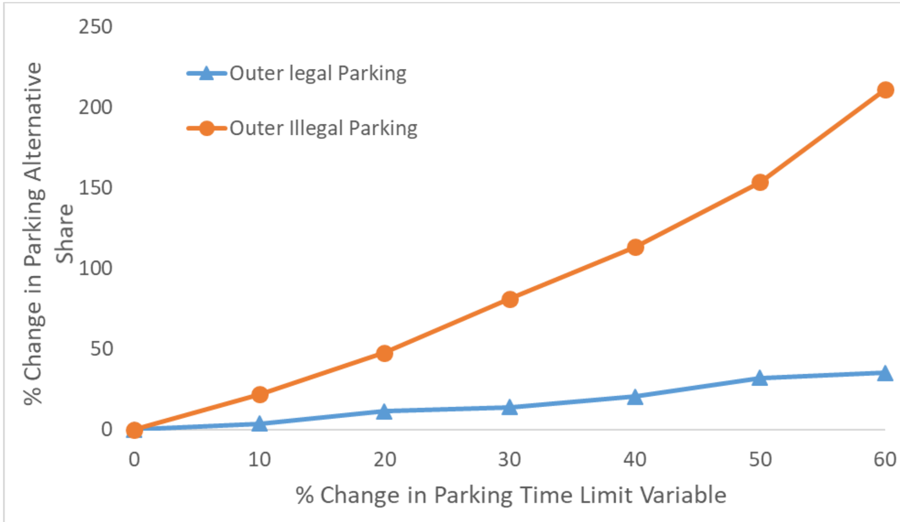

Figure 6. Change in outer-region parking alternative share due to change of parking time limit in conventional parking.

We consider the ratio of driving time to walking time to measure the respondents' preference of relative distance between parking alternatives and destinations. The parameters in both MXL models have a positive sign, meaning that drivers prefer parking alternatives that are closer to the destination. The magnitude of the parameter is larger in assisted parking than in conventional parking. In conventional parking, respondents select a parking spot on their way to the destination because they have limited information about the presence of other parking spaces closer to the destination and more affordable. However, in assisted parking, respondents can select the closest desired alternative among all available alternatives, since all parking information is available.

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 the legal parking cost increases in assisted parking. As illustrated in Figure 7, higher inner legal parking cost results in a much larger drop in the share of inner legal parking with assisted parking than in conventional parking. The availability of parking information is an important aid that allows respondents to find lower cost legal parking spots.

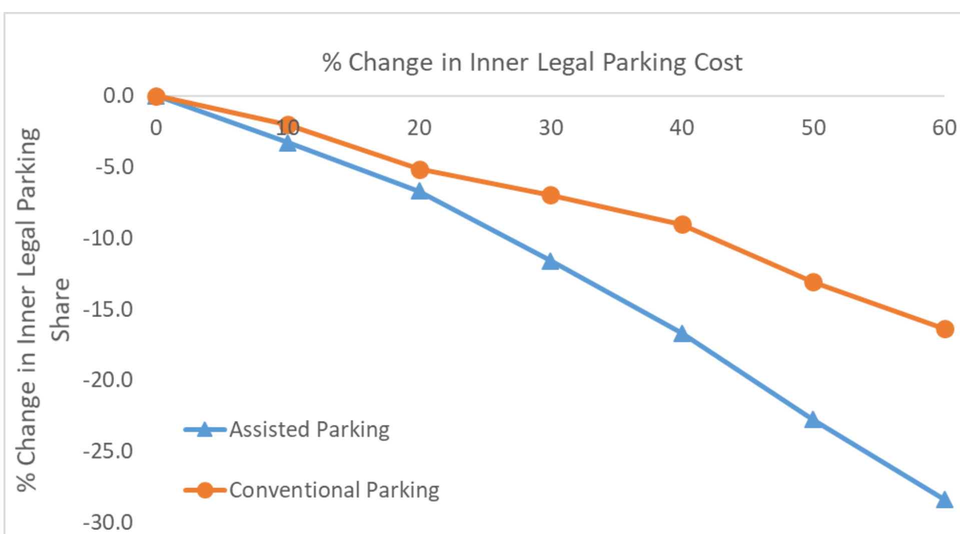

Figure 7. Change in inner legal parking share due to change of inner legal parking cost variable

The parameters for illegal parking citation probability have an expected negative sign because people prefer illegal parking alternatives with low citation probability, which leads to a lower expected cost. The estimated model parameters show that respondents are less sensitive to citation probability increases in conventional parking as compared to the assisted parking model. The reason is the same as the interpretation of legal parking cost sensitivity across the two models. As shown in Figure 8, 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.

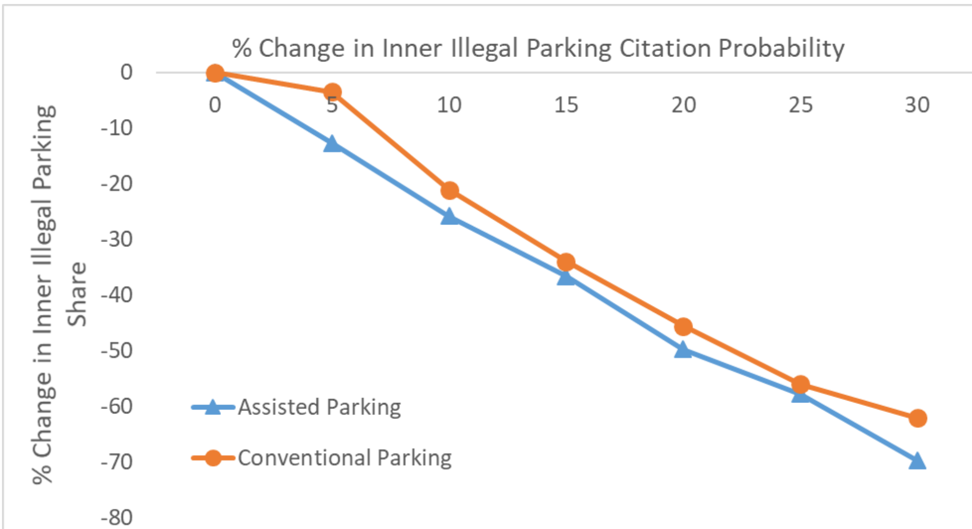

Figure 8. Change in inner illegal parking share due to change of inner illegal parking citation probability variable

We test several demographic factors in the model, such as gender, age, parking search frequency, and income. Although the parking behavior of respondents with different gender and age groups are similar in assisted parking, they are quite different in conventional parking. In assisted parking, most respondents behave similarly, whereas in conventional parking, respondents older than 30 are less sensitive to legal parking cost. The model also indicates that respondents older than 30 are less affected by illegal citation probability. These respondents generally have higher incomes than the younger respondents who are students, which is a reason for their lower sensitivity to the (expected) parking cost. 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 indicates a higher tolerance for risk among males to park illegally, which is also shown in the literature for other aspects of driving as well (Rhodes & Pivik, 2011).

The estimated standard deviations of the random error terms are aimed to capture respondent perception and preference heterogeneity of the alternatives. For legal parking alternatives, the low values indicate that respondent preferences for the alternatives are homogeneous, and thus, the utilities are affected by the explanatory variables. Error terms that have relatively large standard deviations, such as inner-region illegal parking, indicate that the preference heterogeneity is significant. 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 the provided parking information and low time pressure allow respondents to compare alternatives. However, respondents may often consider alternative four as an undesirable alternative since they may not be able to arrive at destinations on time under the high time pressure in conventional parking. Therefore, it results in relatively homogeneous preference and respondent preferences for alternative four are significant only in assisted parking.

6. Conclusions

The main objectives of this paper are to (1) use a parking simulator as an SP survey that involves gamification incentives; (2) model parking choices in the presence of legal and illegal parking alternatives and parking enforcement; (3) analyze parking behavior and driver perceptions of various parking attributes by developing and comparing three different types of discrete choice models, and (4) evaluate the effects of PGI systems on parking behavior.

The findings of this paper are summarized as follows. The gamified survey exposes respondents to simulated hypothetical scenarios. Variables less widely used in other studies could be added in the parking simulation, without causing respondent fatigue, by exposing respondents to the variables in the simulation, rather than showing their values as text, as done in conventional SP surveys. The gamified survey can, therefore, test the combined effect of parking assistance, enforcement, parking price, illegal parking fine, and parking availability, under time pressure.

Three types of logit models are estimated, including MNL, NL and MXL models. The MXL model structure provides the best fitting model and shows that heterogeneity in choice preferences amongst respondents is significant. The MXL model parameter estimates indicate the following. First, the greater time available for the parking task allows people to park in less expensive spots farther from the destination. Second, respondents tend to prefer spots that are close to destinations, especially in assisted parking. The drivers are more likely to select legal parking with relatively low cost in assisted parking. The models also show that respondents prefer low citation probability, especially in assisted parking. Lastly, demographic attributes are found to affect parking choices only in conventional parking. Specifically, people aged greater than 30 are less sensitive to the citation fine, and females are more sensitive than males to the probability of being ticketed for illegal parking.

The estimated choice models show that respondents tend to exercise realistic parking behavior as the estimated model parameters are rational and statistically significant. The rich dataset has potential for future investigation, beyond the estimated models of this paper. In addition to the collected parking choices, the survey collected many other decisions that respondents made during their parking search processes, such as viewed spots, driving routes, and information gathering. Furthermore, the richness of the collected data allows for developing many types of models that capture the dynamics of parking choice, the learning behavior of respondent as they become more familiar with the parking process, or the tendency of the respondents to avoid wrongful activities such as illegal parking regardless of the monetary incentives.

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