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Evaluation of Drivers' Benefits Accruing from an Intelligent Parking Information System

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Abstract

Intelligent Parking Information Systems (IPIS) being implemented in the built environment are regarded as an effective measure for transport management in smart cities. An IPIS improves the efficiency of disseminating real time parking vacancy information and provides convenience to drivers via Apps installed in their smart phones. After giving an overview of various IPISs being applied globally, this research on a typical IPIS is aimed at valuing the benefits to drivers and modeling how variations in the independent variables affect their use. A stated preference approach is presented with a discrete choice survey conducted in Hong Kong with more than 800 valid samples. Contingent Valuation (CV) is applied to evaluate the intangible benefits associated with the use of IPIS, based on the estimation of Willingness-to-Pay (WTP) for its installation with a binary logit model. An aggregated WTP would be useful to policy makers when making decisions to scale up the system. It was found that three factors (*download habit*, *parking time*, and *parking App usage*) have positive impacts on WTP, whereas length of *driving experience* turned out to have a significantly negative influence. The econometric analysis provides useful contributions for the objective assessment of the viability of IPIS projects and their further investment in an emerging smart city environment.

***Keywords**:* Intelligent Parking Information System (IPIS); Intangible benefits estimate; Contingent Valuation (CV); Willingness-to-Pay (WTP); Binary logit model

1. Background

Social, economic, and environmental developments challenge the mobility within a clean and smart city (Ahvenniemi et al., 2017; Colding and Barthel, 2017). The enhancement of sustainability has always been the desired targets in the built environment of a smart city (Ganning, 2014; Zawieska and Pieriegud, 2018). Cruising time increases with parking difficulties (Arnott and Inci, 2006; Van Ommeren et al., 2012). According to Shoup (2006), 30% congestions on average are produced due to cars circulating around buildings for finding parking vacancies in an urban environment. It usually takes at least 3.5 to 14 minutes to find a parking space. This cruising vehicular traffic has produced knotty traffic problems in major cities especially during peak hours for business and major events (Chaniotakis and Pel, 2015). The negative effects of such congestive traffic, such as noise, air pollution and carbon emission, have always beset citizens living or working in the urban centers (Caicedo, 2010). Reducing the congestion and wasteful traffic movements to pave way for a smooth traffic flow is a vital task of the traffic administration bodies (Chaniotakis and Pel, 2015). Furthermore, efficient measures of parking vacancy allocation and utilization can enhance transportation planning and land-use in the built environment (Christiansen et al., 2017). Resulting from a parking policy research in Europe (Mingardo et al., 2015), urban planners, decision makers, and private developers are suggested to closely cooperate and focus more on cost-effective parking measures. Practitioners have been called upon to analyze the under-utilized parking data being held by local authorities (Mingardo et al., 2015). The efficient provisions of different traffic-related services should be integrated in a tailor-made manner to suit each city's characteristics, especially to dovetail the supply and demand for various modes of public transport (e.g., bus and metro systems) with those of private driving (Chowdhury et al., 2018; Mugion et al., 2018). Decision-makers and city planners have responsibilities to achieve optimal accessibility of places, aided by laws, regulations, and especially new technologies (Benenson et al., 2008; Vagnoni and Moradi, 2018; Zawieska and Pieriegud, 2018). Parking fee charges may influence the usage pattern of vehicles, but do not fall within the scope of this study due to its “market goods” characteristics.

[Insert Fig. 1: Functions of an Intelligent Parking Information System]

An Intelligent Parking Information System (IPIS) affords an opportunity to relieve the congestion of parking with the development of Information Communications Technologies (ICTs) (Caicedo, 2010). With a burning need to relieve the problems stemming from car park shortage, an IPIS developed for use by drivers is a burgeoning trend worldwide and is applied to the foreground of smart cities. The rapid development of ICTs brings about important innovations and significant changes to parking. IPIS provides real-time parking vacancies and other useful information to drivers, including alternative available parking spots around the destination and suggestions about the driving routes to the destination (as an option) (see Fig. 1). Taking advantage of wireless positioning, a GPS-based IPIS helps the identification of parking vacancies if the buildings are distributed reasonably evenly within a city. Real-time information of parking availability may then work as a powerful tool to balance supply-and-demand for car parks. As shown in Fig. 2, the real-time vacancy data of participating carparks is manually or automatically fed (through sensors) into a central data saver. Then the data is processed and stored in the “cloud” by the central dissemination network. With the wireless communication network and the base stations, an IPIS utilizes location algorithm to determine the locations of end-users and transmits service requests via mobile terminals. The system processes and pushes updated data of carpark information to drivers’ smart phones or gadgets with installed apps and connected to Wi-Fi. The driving routes to the chosen car parks will also be suggested to the drivers. Then, depending on the systems being used, a reservation request may be sent and confirmed with a feedback message.

[Insert Fig. 2: A typical Intelligent Parking Information System]

The vast progress of the ICT development has given rise to a series of new functions to IPIS for making parking smarter, more convenient and environmentally friendly. IPISs have been applied in many countries with different functions as identified in Table 1. A typical IPIS (Fig. 1) usually provides real-time vacancy information, free booking, navigation (out-door and indoor), and parking fee collection. It can be seen that amongst different functions being provided in different IPISs deployed in major city centers, the real-time information showing the exact locations of vacancies and providing navigational aids to the car parks are the common functions of such systems. Making use of ICT, “Vehicle Information and Communication System” (VICS Center, 2018) is provided in Japan, similar to the “Traffic Message Channel” (Castle Rock Consultants, 1988) in Europe. An IPIS is utilized to transmit data of parking information as well as other traffic and travel (e.g. congestion and collisions) information to road drivers. The types of information provided to drivers by IPIS are depicted in Table 2. Some IPISs also deliver the information of carpark type (multi-storey, covered or open-air), service-time, height limit, contact number, facilities (e.g. Electric Vehicle Charger, installations for the disabled), parking fee and payment methods. Besides, a parking fee collection functions is usually included in an IPIS.

[Insert Table 1: Functions of smart parking systems from worldwide examples]

[Insert Table 2: Information provided to drivers by Intelligent Parking Information Systems]

Governments have been beset by the complexities of smart city appraisals (Lam and Yang, 2017). Evaluation of the effectiveness of various transport alternatives is also a major problem plaguing decision-makers all over the world (Litman and Doherty, 2011). To alleviate the problems, IPISs are being deployed as a smart infrastructure of smart cities all over the world (Karpenko et al., 2018), e.g. those in the US, UK, Netherlands, Singapore, Japan, etc. Cost and Benefits Analysis (CBA) is regarded as the cornerstone of transport appraisal in the EU, the US and Canada for transportation investment. As an rational approach (Boardman, 2011), it helps in the decision-making among alternatives before launching (Lam and Yang, 2017). A well conducted CBA helps in preventing possible controversy on the appraisal and investment in smart mobility projects (European Commission, 2014). Hence, estimation of the benefits and costs should be put on the agenda of IPIS implementation. The costs of

IPIS can be estimated from the quoted price of man-power and purchases from a project budget, requirements and schedules. The values of IPIS projects need to be identified and quantified as far as possible, to provide support in assessing the intrinsic values of such projects towards the achievement of urban sustainable development. For the parking projects, benefits such as reductions in carbon emissions, noise, and time-saving, should be taken into consideration for informed decision-making. Drivers would be the key beneficiaries of this and similar initiatives, whilst the society may benefit from an estimated total time saving of 43 percent and some 730 tons of CO_{2e} emission reduction as seen in San Francisco and Los Angeles respectively (Berg, 2016). Chaniotakis and Pel's research (2015) revealed the usefulness of IPIS and the need to investigate the acceptance levels of drivers and their Willingness-to-Pay (WTP) for such systems.

Given the need to evaluate benefits of IPIS to the individuals, the perceptions of users are intangible due to their benefits not being monetized directly through a buy-and-sell transaction. This is further complicated by possible subjectivity or bias of users. The evaluation is only identified with a vague statement or even ignored by targeted users while responding to assessment requests (Caicedo, 2009; Chaniotakis and Pel, 2015). Little empirical data on the determinants of drivers' perceptions is available. To bridge this knowledge gap, this study aims at developing a scientific approach for the economic valuation of perceptions of drivers towards IPIS. The stated preference approach will be applied with the Contingent Valuation (CV) method to evaluate intangible benefits. A binary logit model will be applied to estimate drivers' benefits as well as examining the independent factors affecting WTP in the econometric analysis. The explanatory variables take into account relevant factors based on previous studies. Through the establishment of logit models, the WTP will be estimated, the statistically significant factors affecting the perception of drivers are determined. This paper contributes to providing insights into IPIS projects to elicit desirable government policy interventions. The approach for estimating the WTP can be incorporated into the benefit assessment of transport projects in order to realize improvements to the surrounding environment in smart city developments.

2. Methodology

2.1 Economic valuation

CV is a widely used stated preference method with a specific hypothetical scene and an accurate description (Mitchell and Carson, 1989). It is meant for evaluating the non-market benefits via a survey-based approach targeted at respondents who are likely to be affected by the hypothetical situation described to them (Bateman et al., 2002). CV works as an econometric technique to monetize the perception on environmental improvement, health, happiness, time-saving, etc. The estimation of equivalent gains (or loss in the case of adverse scenarios) is based on the elicitation of respondents' preference to a hypothetical question about their willingness-to-pay (WTP) to obtain the gain (or willingness-to-accept compensation in case of imposed loss) (Australian Dept. of Finance and Administration, 2006). Besides, the externalities of the IPIS include many aspects with non-market nature, such as carbon-emission reduction, environmental protection, social cost saving, daily-life convenience, life-saving in the case of accident reduction, etc. The econometric models of CV may be effectively applied in analyzing this kind of data to calculate the users' intangible benefits (Relation, 2007).

In the view of Kling et al. (2012), describing the market as a referendum vote is considered as one of the best practices for CV. Most scholars in this area agree with this idea and assert that the statistical approach can be used to apply the decisions solicited from the respondents into formulating economic value distribution (Haab and McConnell, 2002). With the referendum vote, a questionnaire poses a question of WTP according to a hypothetical scenario. WTP is the monetary value of enjoying a benefit or avoiding a harm to an individual (Boardman et al., 2017). In a survey of CV, using an open-ended method, the respondents are simply asked to state their own maximum WTP for acquiring the good, or policy, that is being valued. In comparison, in a closed-ended alternative bidding method, respondents are asked whether they would pay a specified amount for the good or policy that has been described, with a single-bounded or double-bounded iteration. The closed-ended WTP procedure minimizes non-response and avoids outliers (Bateman et al., 2002). Single-bounded is a dichotomous choice (referendum) method, whereby respondents are asked whether they would be willing to pay a particular specified price to obtain a good or policy only once.

The National Oceanic and Atmospheric Administration (NOAA) panel recommended the single-bounded approach to elicit valuation responses in their CV guidelines (Arrow et al., 1993). The single-bounded questioning approach has higher operability and is particularly suitable for collecting and processing data. The WTP estimates derived from dichotomous choice (referendum) method are significantly more effective than those resulting from the comparable open-ended WTP. Thus, the single-bounded approach is applicable to direct questioning due to time limitation and the format of the survey appealing to drivers (who are more likely to be hectic) as the respondents.

The WTP is the proxy to the monetary value of obtaining (or losing) the benefits directly (Bateman et al., 2002). Adopting the parametric approach, WTP can be estimated with a binary logit model. Logit is the appropriate modelling tool for the respondents' choice of "Yes" or "No" when they are asked if they are willing to pay or accept a certain monetary value for obtaining a specified benefit or for bearing with a specified detriment respectively. Hanemann (1984) and Cameron (1988) put forward their respective approaches of parametric analysis. Hanemann (1984) derived the distinct formulation of a logit model to be consistent with the hypothesis of utility maximization. Cameron (1988) proposed that the underlying function for WTP can be constructed via the estimated coefficients. The logistic regression model interpreted with its transformations of the vector of explanatory variables (Kay and Little, 1987) has been accepted as a widely used approach in the environmental valuation field. CV works as an efficient approach to evaluate the intangible benefits in this research. The parametric method is based on logistic regression of the data retrieved from single-bounded referendum as the econometric analysis method.

2.2 Benefits identification

IPIS is one of the more recent smart mobility initiatives with extensive practical value (PwC, 2017). The benefit valuation has complex characteristics with several components. This system reduces wasteful traffic in search for parking vacancies, making the air around buildings less polluted. It benefits a number of relevant parties including drivers, non-drivers, and the services providers (carpark owners). An IPIS enables individuals to improve welfare and efficiency concerning the time saved, acquisition of information, services, and foster interactions. For a parking app, the major beneficiaries are still drivers. Hence the identification and estimation of the drivers' benefits are given priority. Many factors affect the parking behaviors of drivers, such as parking fee, service level, familiarity of the area, and parking habits (Chaniotakis and Pel, 2015). Parking location choice affects the amount of traffic and distribution of traffic flows over the road network. Ommeren stated in his research (2012) that the information improvement of parking vacancy as well as flexible pricing can reduce cruising time. The availability of real-time information on parking vacancy would play an important role in the management of limited parking resources in urban neighborhoods. With an IPIS, the real-time information for parking is delivered for the regulation of traffic flow (in case of jams) and optimization of transportation modes near carparks (Ni et al., 2018). Drivers can check vehicle parking space and service information before driving into a car park entrance, and their driving routes can be optimized by avoiding wasting mileage, time and gasoline consumption. The reduced traffic due to less cruising for parking makes it easier to business to gain higher efficiency in their meetings, operations and transactions. The parking availability at destinations also has impacts on car use significantly, given that shortfalls and restrictions in parking are known in advance (Christiansen et al., 2017). Accidents, air pollution, carbon emission and noise produced with parking space search (e.g., horning to blocking cars and warning pedestrians) may be reduced (Caicedo et al., 2016).

As shown in Table 3, all the intangible benefits are summarized, including market and non-market benefits. The intangible non-market benefits of an IPIS may be estimated through eliciting the preferences of drivers with CV (e.g. time-saving, air purification, carbon emission reduction, and accident reduction, etc.). Petrol cost-saving, and vehicle mileage/depreciation reduction are market benefits, which can be monetized directly, but then the exact amount and effects of these market benefits are sensitive to price changes in different locations and hence may be subsumed in the drivers' WTP by including them in the briefing given to drivers during questioning so that an overall perception value is obtained. Such market benefits may be separately dealt with in principle by collecting mileage statistics, but it is not easy to record the data on the part of drivers, which would end up in a subjective estimate in most cases.

[Insert Table 3: Identification of drivers' benefits]

2.3 Model specification

Use of the parametric method can help to evaluate WTP with the single-bounded questionnaire approach. In a binomial distribution, the dependent variable is the categorical response *Yes/No* to the elicitation question with a proposed bid (Tranmer and Elliot, 2008). Hanemann (1989) advanced the notion that: $Pr\ \{willing\ to\ pay\ B\} \Leftrightarrow Pr\ \ \{true\ WTP > \ B\}$, and B is the proposed bid amount for the respondent to vote ($B = b_{k)},\ and\ \ b_k$ is set to be different bid values (in this case HK$15, 20, 25 or 60; where US$1 = approx. HK$7.8) obtained through a pilot test with a small sample of targeted respondents before the formal survey (Appendix A). The respondents will be required to answer *Yes/No* as to whether they are willing to pay b_k in the mass survey.

The probability of answering *Yes*, denoted as P_i, is the response probability, which may be interpreted in an intuitive approach (Tranmer and Elliot, 2008):

$$P_i = \ \ Pr\ \ (Y = 1|\ \ B, \boldsymbol{X}) \tag{1}$$

where Y is the binary dependent variable, and $Y = \begin{cases} 1, \text{ if answering } Yes; \\ 0, \text{ if answering } No. \end{cases}$ $\boldsymbol{X} \equiv (x_1, x_2, \cdots, x_j),\ x_j$ is the explanatory variable affecting the response. Through the utility-theoretic approach, P_i is determined with the relationship between Y and B, together with the additive combination of different explanatory variables (x_j) (Kay and Little, 1987).

The parametric approach of estimation utilizes discrete response data retrieved from the single-bound discrete choice question (*are you willing to pay an amount B?*) as the dependent variable matching the closest distribution pattern of the logistic equation. Besides the logistic regression model is well established for the analysis of binary response data (Kay and Little, 1987). The logistic distribution is commonly represented as $logit\ \ (P_i) = \ \ ln\ \ [P_i/(1 - P_i)]$ for $0 < P_i < 1$. A general linear model as the equivalent measure of discrete response may be interpreted as follows (Cameron, 1988; Kay and Little, 1987):

$$logit\ \ (P_i) = \lambda + \ \ \mu b_k \tag{2}$$

where λ is estimated with regards to a set of explanatory variables (x_j), and μ is the coefficient of bid (b_k). Based on the presentation in Equation (2), the binary logit model may be transformed to the following equation:

$$P_i = \{1 + \exp[-(\lambda + \ \ \mu b_k)]\}^{-1} \tag{3}$$

According to the Cumulative Distribution Function (CDF) $F(\cdot)$, $F(\theta) = Pr(\theta < B) = \int_{-\infty}^{B} f(t)dt$. WTP is defined with the random variable θ. When the respondent answers *Yes*, the WTP is larger than the bid amount, that is $P_i = P\,r(\theta \geq B)$. With the CDF applied, the distribution of the probability of WTP larger than B can be calculated from solving: $P_i = \ \ Pr(\theta \geq B) = 1 - F(\theta)$. Hence, by the calculation and analysis of the CDF of logistic distribution, the mean value of the distribution can be calculated as λ/μ .

Kay and Little (1987) proposed that the transformation of the vector of explanatory variables in the logistic model was appropriate. Haab and McConnell (2002) also provided the insights that the λ in the linear utility function (Equation (3) may be described by the product of a vector of variables related to individual and a vector of corresponding coefficients. Hence, on the basis of the discrete-response CV method of Hanemann (1984) and Cameron (1988), WTP can be interpreted with:

$$M = \ \ \hat{\lambda}\ \ /\ \ \hat{\mu} \tag{4}$$

where M denotes the mean WTP , $\hat{\lambda} = \boldsymbol{\gamma}\ \ \cdot \boldsymbol{X}$, whereas $\boldsymbol{X}$ is the vector of variables (x_j) with respect to the respondents; $\boldsymbol{\gamma}$ is the vector of estimated coefficients (β_j) corresponding to variables (x_j). $\hat{\mu}$ denotes the estimated coefficient of proposed bids (b_k).

2.4 Survey design

IPIS is implemented as part of the drive in establishing Hong Kong as a smart city with a relatively congested living environment (Central Policy Unit, 2015). The shortage of parking space has always been existed problem in Hong Kong. The IPIS making use of an App at the user end can be easily downloaded and installed in smart phones to provide real-time parking space information on some pilot areas of Hong Kong, with anticipation for it to be extended to cover the urban areas of the entire city in future for free regular use. Although there are carparking apps developed by private carpark owners, this study is based on an App of IPIS developed by the Hong Kong government. The system configuration is similar to Fig. 2 as described above, which is commonly adopted in many parts of the world, including Singapore and the UK. A survey of the IPIS was conducted among drivers, and the target samples were drawn from full driving license holders in Hong Kong. The empirical analysis also intends to provide insights into the determinants of the WTP as perceived by drivers regarding the IPIS.

The survey of CV is based on a hypothetical scenario described in full, including proposed payment methods to instill realism on the respondents. The expenses mentioned in the question for the use of the Apps were made clear to be purely hypothetical as a valuation proxy. The questionnaire includes a demographic section, containing questions for reflecting the behavioral patterns. The single-bounded approach (i.e., one value being asked one time for each respondent) was used to solicit the WTP. The parametric model would enable the factors influencing WTP to be identified.

A series of pilot interviews was carried out through 30 face-to-face interviews before the formal survey to pre-test the questionnaire, especially the establishment of proposed bid values for the elicitation question to derive the mean WTP (Bateman et al., 2002). The interviews were conducted amongst respondents having a wide range of status and characteristics (including professional drivers, engineers, teachers, etc.) to derive a suitable range of bid values for inclusion in the questionnaire for the mass survey.

The finalized questionnaire contains both the demographics and alternative questions (one bid value inserted in each version; and there were 4 bid values), which were integrated in an anonymous format. Ethical clearance was obtained from the University for administering the survey with a sample of members of the public, including drivers with registered parking lots in three local universities and three residential estates spread over Hong Kong geographically (hereinafter called the “former group”) as well as drivers who attended two licensing offices of the Transport Department in Hong Kong (for their license renewals – hereinafter called the “latter group”). A QR code printed on a colorful card was provided for the former group to access a web-link hosted at the university online portal, and a hardcopy was administered face-to-face by a research student with the latter group. Two questionnaire versions in English and Chinese were made available. The respondents were firstly asked a question to identify themselves as licensed drivers (or otherwise), and they were given a brief description of the IPIS in the questionnaire, so that they could understand and answer the related questions about the system in an unambiguous manner. The survey was conducted in Hong Kong from June 2017 to September 2018.

Following the published guidelines for optimal bid design (Haab and McConnell, 2002), the distribution of the WTP was devised from 30 pre-tests. Since 19 out of the 30 respondents chose the second column listed in Appendix A, the interval of HK$10~30 was chosen as the range of the possible WTPs. Besides, HK$60 is also set as a bid value to cover all eventualities because 6 pre-test respondents chose the third column of the bid ranges. Thus, the alternative amounts (HK$15, 20, 25 or 60) were identified as the reasonable bids for the respondents to vote (one bid value appearing in one questionnaire only). A sample of the questionnaire (with alternative bid value of HK$20) is included as Appendix B to this paper. Besides, this investigation surveyed nearly equal number of valid samples of different proposed bids (HK$15, 20, 25 or 60) (see Table 4).

[Insert Table 4: Valid samples versus bid values]

To enable empirical analysis, the questionnaire also included related co-variates affecting drivers’ WTP. Several independent variables were included based on possible factors which may affect drivers’ attitudes towards IPIS, as gleaned from the above background study. As depicted in Table 5, the questionnaire includes four subsets of attributes: demographics (*gender, age, education*) (Waerden et al., 2015), habit (*online habit*- having online payment habit or not, *download habit*) (Bamberg et al., 2003), experience (*driving experience*, *GPS usage*- using navigational maps or not, *parking App usage*) (Antolín et al., 2018), parking demand (*weekly driving-time*, *parking time, parking frequency, alternative car park in mind*) (Ibeas et al., 2014; Lam et al., 2006).

[Insert Table 5: Description of co-variates]

3. Analysis and discussion

3.1 Descriptive statistics

As shown in Table 6, a total sample size of 1205 was obtained, 378 with missing answers and 827 are valid, which should be representative of the Hong Kong driving population (about 2.3 million (Transport Department, 2018)), following the CV sample setting of Mitchell and Carson (1989). Having knowledge of the high demand for parking spaces in Hong Kong, licensed drivers were selected as the target group of potential users of IPIS. The majority of the samples in the survey are male respondents (79.6%) in the age range of 18 ~ 60 (92.6%), which represents the main body of motorists in Hong Kong. A majority (66.6%) had more than 10 years' driving experience. It can be seen that the education levels of the samples tend to be on the high side, but this fits the purpose of the survey. Drivers with lower educational levels (15.3%) were most likely bus, truck or taxi drivers who do not need to search for parking spaces in the course of their daily routine since they drive on the road continuously, parking only in depots when they rest. They may not regard the usage of IPIS as important in most situations. On the contrary, drivers with a higher educational level (84.7%) made up the majority of the samples and, being drivers for business, family matters and leisure, they are potential users of the IPIS system. The sampling frame is appropriate for the nature of this investigation of IPIS.

[Insert Table 6: Demographics of Respondents]

The socio-demographic profile of the respondents is depicted in Table 7. The mean frequency of them using e-services or mobile services in daily life, such as online shopping, mobile map, etc., is 3.63 (the score range is 0~5 from *never* to *always*), with 79.1% respondents having a score of more than 3. This relative high score of the habit of using online services reflects the rapid adoption of new technologies, especially smart phones being widely used in daily life. 83.4% respondents had used GPS navigation system (in smart phone or installed in car) in their driving. It shows that navigational technology was widely used by the drivers. The function of navigation has been included in many typical IPISs, which demonstrates the high level of awareness about this kind of system.

[Insert Table 7: Socio-demographic profile]

The individual number of times taken to seek parking space is 3.37 on average per week, which shows the severity of wasted traffic and congestions caused by cruising for parking space, as well as the huge needs for efficient tools to help look for parking vacancies. Just 13.3% respondents had in mind other alternative car parks (before any parking APP was available) when driving to a carpark near to the destination and the entrance says "full", which shows the usefulness of the IPIS to the drivers.

In addition, the score of *Parking time* (the time spent to seek a parking space) is 2.3 (the grade range is 0~5 from *less than 5 minutes* to *more than 20 minutes*) on average, hence the time taken in parking can be taken as 10~15 minutes approximately. With the mean parking frequency being 3.37 per week, the total time-saving is 33.7~50.6 minutes, roughly more than half an hour every week. Hong Kong is a fast-paced international metropolis. The time saving of more than half-an-hour is important for the busy citizens in Hong Kong, and in similar cities.

3.2 Modelling

Through the parametric approach, three econometric models were generated with the influential factors identified in Table 8. The model construction was subsequently accomplished by using relevant principal constituents of Stata 14.0 statistically (STATA, 2017). The extent of the impacts is interpreted relatively through the coefficients of the statistically significant variables. The coefficients normalized for comparison are presented in Table 8 for the three models. The signs of the coefficients determine the trends of the influence on the dependent variable. The factors' contribution to the utility is depicted clearly through the three logit models.

[Insert Table 8: Econometric models]

From Model I (whereby all variables were put in as explanatory variables), it can be seen that the estimated coefficients of *bid* are highly statistically significant and negative, reflecting their counteracting negative effects on the probability of a certain WTP being accepted. In the parametric modelling, all attributes of the respondents (demographics, habit, experience, and demand) in the questionnaire are included as the explanatory variables of the binary logit model (Table 9). The econometric modeling identifies the statistically significant determinants of the acceptance of bids as well as the relative extent of their influence through the normalized coefficients. *Download habit* has a positive (also the highest normalized value) coefficient (0.451), meaning that drivers who are used to online transactions are more inclined to have a higher WTP for IPIS. *Driving experience* had a negative coefficient estimate (-0.279), which is because more experienced drivers should be more familiar with the parking places available and thus, they had less need for IPIS. The positive coefficient estimate (0.376) of *parking App usage* reflects users' perceived usefulness of the IPIS for checking vehicle parking space before driving to their destinations. The positive coefficient (0.217) of *parking time* indicates that those who spent more time to seek a parking vacancy would have a higher tendency to pay more for the parking apps.

[Insert Table 9: Significant variables profile]

In Model II, the significant factors in Model I (*download habit*, *driving experience*, *parking App usage*, *parking time,* and *bid*) are imported as the explanatory variables. The modelling results show that all these factors are highly significant in Model II except *Parking App usage*. Then, the highly significant factors in Model II (*download habit*, *driving experience*, *parking time,* and *bid*) are imported in Model III. The analysis with the binary logit models indicates that two factors (*download habit* and *parking time*) have positive impacts on WTP, together with the negative influence of *driving experience* and *bid*. Consistency is shown is the signs of the coefficients, indicating that the positive and negative influences of the determinants are prevalent among Model I, II and III.

3.3 Mean WTP estimation

The mean WTP is estimated to represent a monetary value of the individual benefits to the drivers. In the three econometric models shown in Table 8, the estimated coefficients of *Bid* are all negative and highly statistically significant ($p<0.001$). The calculation results based on the binary logit models are shown in Table 10. Model I is constituted with all the socio-demographic variables in the questionnaire. In this model, the mean WTP is calculated as HK$28.4 (US$3.6)[1], and the 95% confidence interval of mean WTP is HK$26.3~30.5 (US$3.3~3.9). Then the significant factors are identified and imported in Model II to get a more rigorous result (HK$28.3) and interval (HK$27.1~29.6). Finally, Model III is established with only the highly statistically significant factors[2]. The determinants (*download habit, driving experience,* and *parking time*) are specified as the only explanatory variables in Model III. The mean WTP result (HK$28.2) and interval (HK$27.3~29.2) converge with the other models.

[Insert Table 10: The estimation of mean Willingness-to-pay for IPIS]

As depicted in Table 8 and Table 10, the 3 models are in alignment with different dimensions of habit, experience, and demand as the related parameters. It is noted that despite different explanatory variables were imported in the 3 models, sufficiently close and consistent results of the mean WTP are estimated at US$3.6 approximately. Triangulating the 3 models, the widest interval of mean WTP is HK$26.3~30.5 (US$3.3~3.9), which is near to the range covered by the proposed bids (HK$15, 20, 25, 60). This is an indirect verification of the rationality of the bid levels setting. The validity of the empirical approach of CV is demonstrated by the survey data and estimation results.

This study adopts a systematic approach to estimate the perceived benefits of drivers towards the IPIS. The total benefits for the drivers is estimated at US$8,206,798 (based on the US$3.6 as the individual WTP) with the 2,279,666 full driving license holders in Hong Kong at the end of September 2018 (Transport Department, 2018). The latter number is expected to grow continuously.

4. Discussion

4.1 Analysis and finding

[1] 1US$=7.85HK$.
[2] Statistically significant at or even lower than the level of 0.001.

The results of mean WTP are close among Model I, Model II, and Model III. Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978) are criteria used in comparative statistical techniques providing objective functions to rank the fitness of models (Posada, 2008). The estimates of AIC and BIC show the performance and of Model I, Model II, and Model III. From the results of AIC/BIC in Table 8, Model III is the optimal estimated model with the mean WTP calculated at HK$28.2 (US$3.6) (see Table 10) based on the comprehensive optimal configuration of fitting accuracy and number of parameters. Meanwhile, the estimates of Model II and Model III do not perform significant difference in terms of AIC/BIC, which is in good agreement with the two models' close mean WTP calculated. From another point of view, Model I yield a 95% confidence interval as HK$26.3~30.5 (US$3.3~3.9) (see Table 10), it is reasonable to adopt this result with the widest interval as the estimated interval of mean WTP with preferred conservatism in the benefit valuation.

Beyond that, to reduce potential biases, best practice protocols (Kling et al., 2012) have been applied in design and implementation of CV surveys. With a reliable survey, the results of CV may be acquired with validity (Hanemann, 1994; Kling et al., 2012). Sufficient pre-testing has been conducted for the design of the survey including the contents of questionnaire and the bidding method, the vote values etc. This investigation also depicts IPIS and its benefits clearly to make sure that the respondents understand and take note of the information that was provided to them. This investigation is based on a larger sample size (1,205 in total) in comparison with 400 samples considered as suitable for a CV survey in a city as depicted in Mitchell and Carson research (1989) to value public goods with CV. This survey results were supported by more than adequate samples with four groups of respective bids.

Thus, the drivers' benefits of IPIS are depicted through estimating the WTP. Firstly, suitable variables were identified through the literature and pilot testing; secondly, a comprehensive questionnaire to conduct a survey with sufficient samples was designed; thirdly, logit modeling through regression was conducted; and finally, the WTP and influential factors were derived after a comprehensive analysis of 3 related models.

4.2 Policy implications

The monetized benefits can be applied in the Cost-and-Benefit Analysis for the investment plan of smart city projects (which are usually dealing with non-market goods) at the preliminary stage. An economic assessment framework entails the impacts of various costs and benefits to be reflected in the overall analysis. This estimation of the benefits as perceived by drivers is essential for the decision-making. The intangible benefit values may be set against the costs of developing and operating an IPIS to gauge its financial feasibility.

Besides, it was found that four influential factors (*download habit*, *driving experience*, *parking time*, and *parking App usage*) have significant impacts on WTP. Habits often affect the behaviors of consumers directly. 60.5% of the respondents have not ever paid for downloading any APP through their mobile phones yet. This implies that they were not accustomed to paying for App downloading, even for an IPIS. The habit of downloading priced Apps into mobile phones may engender a new digital divide of ICT use, which produce negative effects on the promotion of IPISs, even though they are usually free of charge. Relevant real-life experiences towards driving, parking and parking App usage influence the perception of drivers towards IPIS significantly. Just 13.3% of the sample had ever used similar Apps of IPIS for checking vehicle parking space before driving to their destinations. Hong Kong is at the beginning stage of becoming a smart city. Hence, the application of IPIS is still at the initial stage. The positive effect of past APPs usage implies that active promotion to non-app-using drivers may yield a higher level of adoption of IPIS. If the IPIS is promoted further, the WTP may be higher in the near future. Time to seek parking space is positively correlated with the benefit perception of drivers towards the IPIS. This empirical finding tallies with previous economic behavioral research on the specific variables of parking being time and location, etc. (Ibeas et al., 2014; Lam et al., 2006). The predominance of parking time indicates the strong demand for a parking vacancy search tool worldwide.

In the context of smart cities, the incremental intangible benefit estimation may be used for the comparison of alternative projects. If the projects' capital and recurring expenditure budgets were provided for technology-focused public endeavors with a competitive bidding program, the net present values can be derived for the projects' operational periods. The approach for estimation of drivers' perceived benefits as shown in this research allows the rapid justification of resources meeting the prime concern of public investment needs.

4.3 Further research

This study focuses on the valuation of intangible benefits to drivers, excluding the benefits accruing to non-users. In fact, non-users also enjoy the benefits from IPIS indirectly. The general public, as non-users benefit from enhanced walkability when crossing streets, a decrease in traffic accidents, congestion reduction, air purification, noise reduction around carpark, etc. As the spill-over effects of externalities should also be considered in a full CBA, non-users' perceptions may be investigated in further research. Other externalities of the IPIS may include more business for the shopping centers participating in the parking information systems because of increase d patronage due to the parking service. This is even more evident with exclusive provision of parking information by the car park premises' developers, in that an exclusive IPIS provides a chance to bring more customers to the shopping malls, thereby generating more sales and profits. In addition, the installation of an IPIS may entail the smart phone and internet upgrading, such as to 5th generation wireless systems with a higher speed of processing. This would an enticing factor for drivers to upgrade their phones and connection plans, again promoting new sales. Whilst the externalities to non-users are wide ranging and it is difficult to evaluate them quantitatively, a clear boundary needs to be drawn for a practical CBA.

5. Conclusion

Based on the benefit study of an intelligent parking information system in Hong Kong, this research demonstrates an approach for evaluating the perception of drivers, which would serve as a useful reference for decision-making in project appraisal. A reliable intangible benefit evaluation method is depicted. The dominant attributes included in this research are based on the literature, and the investigation has identified the determinants affecting WTP with empirical evidence from a large random sample of drivers collected for the first time. These include *download habit*, *driving experience*, *parking App usage*, and *parking time*. The exploration into a viable project evaluation method based on a stated preference approach has been put forward. The results also highlight possible promotion strategies of IPIS, since knowing the influential factors affecting WTP, the target groups of potential App users may be identified with increased certainty. Municipal authorities may monitor and take action in time for efficient deployment of ICT resources. The benefit estimation of drivers towards IPISs enables more rational decision-making and may be used in publicly-invested project appraisals. With the rapid development of ICTs, fruitful functions together with a wider variety of benefits will emerge for the IPIS, and the valuating approach depicted in this paper is a suitable way to estimate its benefits. Besides, the intangible benefits of other smart mobility projects can also be evaluated through the estimating the WTP as depicted in this research.

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Figs.

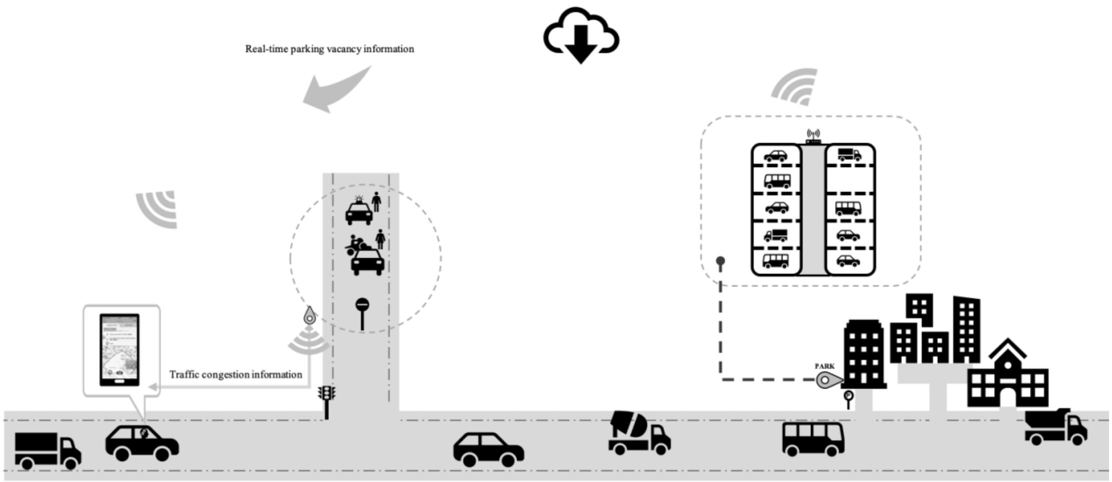

Fig. 1. Functions of an Intelligent Parking Information System

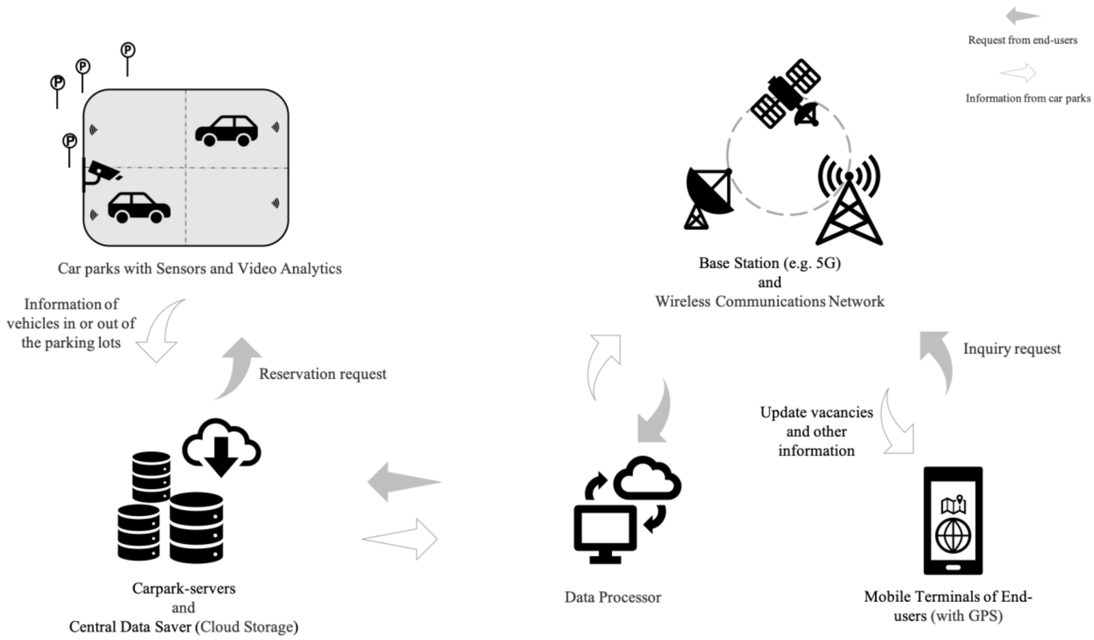

Fig. 2. The typical Intelligent Parking Information System

Table 1. Functions of smart parking systems from worldwide examples

Country or Region	Typical System	Typical functions			
		Real-time information	Parking fee collection	Booking	Navigation (Out-door or In-door)
US	System U	√	√	-	√
UK	System K	√	-	-	√
Italy	System I	√	√	√	√
Netherlands	System N	√	√	√	√
Singapore	System S	√	√	-	√
Japan	System J	√	√	-	√
Hong Kong	System H	√	-	-	√

(Note: Trade names of IPIS are excluded to avoid commercialism)

Table 2. Information provided to drivers by Intelligent Parking Information Systems

Information provided to the drivers	Real-time parking vacancy information;
	Navigational aids;
	Other traffic and travel (e.g. Congestion and collisions) information;
	Carpark type (multi-storey or not, covered or open-air);
	Service-time (e.g. 24hr);
	Height limit;
	Carpark contact number;
	Facilities (e.g. electric vehicle charger, disabilities);
	Parking fee;
	Payment methods;
	Other information.

Table 3. Identification of drivers' benefits

Benefits to the drivers	Non-market benefits	Overall traffic volume reduction	Congestion reduction
			Traffic accidents decrease
			Time-saving / Efficiency / Convenience
		Environmental sustainability	Greenhouse gas reduction
			Air purification
			Noise reduction
			Water / Land use / Other recourses protection
	Market benefits	Gasoline-saving	
		Reduce vehicle mileage / depreciation	

Table 4. Description of co-variates

	Variables	Definition	Description
Demographic	Gender	Dummy variable.	1 = *Female*; 2 = *Male*
	Age	Age range of the respondent.	1 = *18 ~ 30;* 2 = *31 ~ 45;* 3 = *46 ~ 60;* 4 = *Above 60.*
	Education	Educational level of the respondent.	1 = *Primary education*; 2 = *Secondary education*; 3 = *Post-secondary*; 4 = *University and above*; 5 = *Others*.
Habits	Online habit	The habit of using online services.	1= *Never*; to 5=*Always*.
	Download habit	Whether the respondent has the habit of downloading priced Apps into mobile phones; dummy variable.	1 = *Yes*; 0 = *No*.
Experience	Driving experience	The driving experience of respondent.	1 = *Not at all*; 2 = *Less than 1-year*; 3 = *1 ~ 3 years*; 4 = *4 ~ 10 years*; 5 = *More than 10 years*.
	GPS usage	Whether the respondent has used GPS navigation system; dummy variable.	1 = *Yes*; 0 = *No*.
	Parking App usage	Whether the respondent has used App for checking vehicle parking space; dummy variable.	1 = *Yes*; 0 = *No*.
Demand	Weekly driving-time	The weekly driving-time of the respondent.	1 = *Less than 1-hour*; 2 = *1~5 hours*; 3 = *6 ~ 10 hours*; 4 = *11 ~ 15 hours*; 5 = *More than 15 hours*.
	Parking time	The time spent to seek a parking space on average.	1 = *Less than 5 minutes*; 2 = *6 ~ 10 minutes*; 3 = *11 ~ 15 minutes*; 4 = *16 ~ 20 minutes*; 5 = *Others*.
	Parking frequency	No. of times to seek parking space on average per week.	Number of the times
	Alternative car park	Whether the respondent has other alternative carpark in mind if no parking space is available at a destination; dummy variable.	1 = *Yes*; 0 = *No*.
Bid		The proposed bid values to be voted.	HK$15; HK$20; HK$25; HK$60.

Table 5. Valid samples versus bid values

Sub-sample (based on proposed bid levels)	Number	Percent (%)
HK$15	205	24.8
HK$20	204	24.7
HK$25	206	24.9
HK$60	212	25.6
Valid samples	827	100

Table 6. Demographics of Respondents

Variables	Classification	Frequency	Percent (%)
Gender	Female	169	20.4
	Male	658	79.6
Age	18~30	110	13.3
	31~45	285	34.5
	46~60	371	44.9
	Above 60	61	7.4
Education level	Primary education	6	0.7
	Secondary education	120	14.5
	Post-secondary	117	14.1
	University and above	584	70.6
Total		1205	
Missing Cases		378	
Valid samples		827	
Effective percentage			68.6

Table 7. Socio-demographic profile

Variables	Mean Score	Standard Deviation
Gender	-	-
Age	2.46	0.814
Education	3.55	0.763
Online habit	3.63	1.146
Download habit	0.4	0.489
Driving experience	4.42	0.945
Weekly driving-time	2.69	1.31
GPS usage	0.83	0.372
Parking App usage	0.13	0.34
Parking time	2.3	1.004
Parking frequency	3.37	3.722
Alternative car park	0.57	0.495

Table 8. Econometric models[a]

Variables	Model-I[c]		Model-II[c]		Model-III[c]	
	Estimate-I ($\hat{\beta}_j$)	Std. Err.	Estimate-II ($\hat{\beta}_j$)	Std. Err.	Estimate-III ($\hat{\beta}_j$)	Std. Err.
Gender[b]	0.166	0.185				
Age	0.167	0.107				
Education	0.021	0.099				
Online habit	0.023	0.068				
Download habit[b]	0.451**	0.154	0.430***	0.149	0.448***	0.149
Driving experience	-0.279**	0.097	-0.205***	0.078	-0.214***	0.077
Weekly driving-time	-0.043	0.065				
GPS usage[b]	-0.076	0.206				
Parking App usage[b]	0.376*	0.220	0.354*	0.216		
Parking time	0.217**	0.073	0.221***	0.072	0.227***	0.072
Parking frequency	0.019	0.021				
Alternatives car park[b]	0.150	0.146				
Bid	-0.020***	0.004	-0.019***	0.004	-0.018***	0.004
Constant	0.221	0.632	0.723*	0.414	0.756**	0.413
χ^2	43.11		37.51		34.82	
AIC	1.37		1.36		1.36	
BIC' [d]	44.22		-3.92		-7.95	

[a] The model is based on binary logistic regression. Variables denote the factors affecting WTP, and the coefficients are related to influence degrees.
[b] Dummy variable.
[c] The significance level of *Prob > Chi*^{2} is lower than 0.001, which suggests that the overall model fits well.
[d] Difference of Model I and Model II: 48.14 in BIC' provides very strong support for Model II;
Difference of Model II and Model III: 4.03 in BIC' provides positive support for Model III;
Difference of Model I and Model III: 52.17 in BIC' provides very strong support for Model III.

* Statistically significant at 0.1 level.
** Statistically significant at 0.05 level.
*** Statistically significant at 0.01 level.

Table 9. Significant variables profile

Variables	Classification	Frequency	Percent (%)
Download habit	Yes	327	39.5
	No	500	60.5
Driving experience	Not at all	5	0.6
	Less than 1-year	52	6.3
	1~3 years	82	9.9
	4~10 years	137	16.6
	More than 10 years	551	66.6
Parking App usage	Yes	110	86.7
	No	717	13.3
Parking time	Less than 5 minutes	193	23.3
	6 ~ 10 minutes	319	38.6
	11 ~ 15 minutes	206	24.9
	16 ~ 20 minutes	95	11.5
	Others	14	1.7

Table 10. The estimation of mean Willingness-to-pay for IPIS

	Model	Valuation HK$ (US$)	95% confidence interval HK$ (US$)
	Model-I	28.4 (3.6)	26.3 ~ 30.5 (3.3 ~ 3.9)
Mean WTP[a]	Model-II	28.3 (3.6)	27.1~29.6 (3.4~3.8)
	Model-III	28.2 (3.6)	27.3~29.2 (3.5~3.7)

[a] US$ are presented in parentheses, US$1=HK$7.85.