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Modeling user perception of public bicycle services

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Abstract

For them to become an alternative to more traditional forms of public transport, public bicycle systems need to be efficiently managed and aimed towards sustainable mobility. A methodology is proposed to achieve this by modelling the standard of quality perceived by users of these systems through the consideration of systematic variations in their perceptions. Ordered Probit models have been calibrated to quantify the change in overall service quality perception when improvements are made to the individual attributes defining it.

Keywords: Quality; Public Bicycles; Ordered Probit;

1. Introduction

Many and varied public bicycle schemes have appeared over recent years to offer public transport aimed at promoting sustainable mobility. The public bicycle is still a relatively new mode of transport with many positive characteristics in favour of its exploitation and integration on a much wider scale. The first step towards achieving maximum use of available resources is the characterisation of the users and the journeys they make along with the modelling of the perceived quality of the service currently being provided.

A review of the international scientific bibliography shows that Ordered Logit and Probit are the discrete choice models that more efficiently characterise the quality of different transport systems and which also provide knowledge for use in future policy design (Hensher et al., 2010; dell'Olio et al., 2010). In social sciences, quality related research is often carried out with ordered scales of data, being this an essential characteristic in the dependent variable of Ordered models. Some discrete choice models have included their own quality index created from the variables of the transport service being studied (Debrezion et al., 2009) and others have used regression models with user satisfaction data (Givoni and Rietveld, 2007). Other proposed quality indexes have worked with indicators of the characteristics corresponding to the modelled transport service (Eboli and Mazzula,

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2009). However, none of these methods has yet been applied in the study of perceived quality in public bicycle lending systems, which is the major contribution of the work presented in this article.

The bicycle has of course been the subject of a wide range of research, but from other points of view, such as the factors influencing bicycle use and route choice (Wardman et al., 2007; Pucher and Buehler, 2008; Su et al., 2010). The role of infrastructure in the demand for cycling has been approached in depth and by a variety of methodologies (Dill, 2003; Akar y Clifton, 2009; Dill, 2009), concluding that demand is largely related to safety factors associated with this mode of transport.

The design and management of public bicycle systems needs to have detailed information about the journeys being made in urban areas and the users' characteristics. Barcelona (Froehlich et al., 2008), Lyon (Borgnat et al., 2011) or London (Lathia et al., 2012) have been analysed in this sense, with the latter concentrating on casual system use. Dell'Olio et al. (2011) calculate the potential demand derived from the introduction of a public bicycle system and the optimization of pick-up and drop-off points. Another methodology for calculating the location and number of docking stations required by a given system was proposed by Lin and Yang (2010) from origin and destination data.

This article is structured in accordance with the phases of research carried out. Section 2 presents the methodology followed for modelling the quality of service users perceive from a public bicycle system and its application to the city of Santander has provided the results presented in section 3. The discussion about the calibrated models is presented in section 4 and the main conclusions in section 5.

2. Methodology

Discrete choice models are based on random utility theory which provides information on an individual's behaviour when faced with a choice process and subjected to certain socio-economic characteristics and journey constraints. The perception of quality responds to the same choice process, in this case, one of evaluating or qualifying according to a range of available possibilities on an ordered scale. The definition and study of the quality provided by a public bicycle service based on this scale recommends the use of an Ordered Logit model as the ideal modelling tool given the demanding discrete and ordered nature of the dependent variable. Since their definition in 1975 by McKelvey and Zavoina, ordered models have been used in a range of applications associated with data arranged in rankings, qualifications or levels.

The Ordered model has a regression format in which the dependent and unobservable variable y^* is a linear function of a group of independent variables x_i and a random term ε.

$$y_i^* = \beta' x_i + \varepsilon_i,\ \varepsilon_i \sim F(\varepsilon_i \mid \Theta), E[\varepsilon_i] = 0, Var[\varepsilon_i] = 1$$

The discretization of the variable y^* is done using the following equations:

$$\begin{aligned}
&y = 0, if\ \ \mu_{-1} < y_i^* \leq \mu_0 \\
&y = 1, if\ \ \mu_0 < y_i^* \leq \mu_1 \\
&y = 2, if\ \ \mu_1 < y_i^* \leq \mu_2 \\
&\dots \\
&y = J, if\ \ \mu_{J-1} < y_i^* \leq \mu_J
\end{aligned}$$

The parameters to be estimated by the model are β' and μ. β' are the weights associated with each explanatory variable and represent the importance of each one in the dependent variable. The parameters μ are the limits which define the variable y.

The random term ε represents the error, which is assumed to have a zero mean and a unitary variance.

The calibration requires a group of normalisations: the value of the first answer y corresponds to 0, the lowest threshold parameter corresponds to -∞ and the greatest to +∞. Finally, μ_0 is equal to zero.

The value scale designed in the survey has the following options: “very bad”, “bad”, “neither good nor bad”, “good” and “very good”. The model works with an ordinal scale and as its estimation requires the representation of all the replies, the negative valuations “very bad” and “bad” had to be grouped together in the same ordinal numerical category. The applied model has the following structure:

$$y_i^* = \beta' x_i + \varepsilon_i,\ \varepsilon_i \sim F(\varepsilon_i \mid \Theta), E[\varepsilon_i] = 0, Var[\varepsilon_i] = 1$$

$y = 0$, (”Very bad” or “Bad”), if $-\infty < y_i^* \le 0$

$y = 1$, (”Neither good nor bad”), if $0 < y_i^* \le \mu_1$

$y = 2$, (”Good”), if $\mu_1 < y_i^* \le \mu_2$

$y = 3$, (”Very good”), if $\mu_2 < y_i^* \le +\infty$

The model estimates the probability of observing each result of y =0, 1, 2, 3, a characteristic which differentiates it from multiple regression, which doesn’t work with probabilities, and directly estimates an average value of the dependent variable based on the observed values.

The probability associated with the observed results estimated by the ordered model is as follows:

$$P[y_i = j \mid x_i] = P[\varepsilon_i < \mu_j - \beta' x_i] - P[\mu_{j-1} - \beta' x_i],\ j = 0,1,2,3$$

There are two types of ordered models, the ordered probit model, where the random component ε_i distributes Normal, and ordered logit, where ε_i presents a log distribution of zero mean and a variance of $\pi^2/3$.

The series of probability functions associated with each result y_i is given by the following expression:

$$P[y_i = j \mid x_i] = F[\mu_j - \beta' x_i] - F[\mu_{j-1} - \beta' x_i] > 0,\ j = 0,1,2,3$$

The parameters are obtained using the process of maximum likelihood. The optimisation is supported by using log likelihood, which is the logarithm of the probability expression above:

$$\log L = \sum_{i=1}^{n} \sum_{j=0}^{j} m_{ij} \log[F(\mu_j - \beta' x_i) - F(\mu_{j-1} - \beta' x_i)],$$

where m_{ij}=1 if y_i=j, and 0 in other cases.

The interpretation of the Ordered model is not the same as with a regression. The estimated parameters do not report on the final result, they provide a general vision about how the users feel. Partial effects are used to interpret the parameters; these are based on the probabilities of the choice model:

$$\delta_j(x_i) = \frac{\partial P(y = j \mid x_i)}{\partial x_i} = [f(\mu_{j-1} - \beta' x_i) - f(\mu_j - \beta' x_i)]\beta$$

The partial effects report on the effect a change in a variable has on the probability of a specific result for y. The values of these effects could be either positive or negative depending on whether they imply an increase or decrease in the probability of choosing each alternative for y.

The accumulated value of the partial effects of all the variables is also of interest:

$$\frac{\partial P(y \le j \mid x_i)}{\partial x_i} = \sum_{m=0}^{j} [f(\mu_{m-1} - \beta' x_i) - f(\mu_m - \beta' x_i)] = -f(\mu_m - \beta' x_i)\beta$$

The models calibrated for modelling the quality perceived by users from a public bicycle system represent the process of evaluating this quality from a limited group of predefined variables x_i collected from each of the interviewed users. The choice of these variables is relevant because they are used to explain the choice process that needs to be modelled. The thorough review of the international literature along with the Focus Groups made up of users and none users of public bicycles justify the factors included in the pilot survey. The collected data are analysed and modelled to check the validity of the different variables. Finally, the definitive survey is designed which provides the input data for the final models. The survey was of the RP type (Revealed Preferences), consisting of a series of questions about users' experiences of the existing system. The user is initially asked to provide a score for the overall service they receive and is then asked about the valuation they would place on a group of variables set up to define the public bicycle service. The use of discrete choice models allows interactions to be introduced which can, in many cases, explain the different perceptions of the users, possibly originating in socioeconomic factors or journey restrictions, data which has also been collected in the survey (Ortúzar and Willumsen, 2011). Dell'Olio et al. (2010) concluded that the overall quality of a system is perceived differently at the beginning of a survey from after having scored specific aspects of it. The potential for explaining choice mechanisms from the perceptions being provided at different stages of the survey is why both evaluations (*Iv* and *Fv*) were asked for in this survey.

3. Results

The methodology presented here has been put into practice in Santander (Spain), capital of the Autonomous Community of Cantabria, one of 17 in Spain and located on the north coast. Santander is a medium sized city, covering 36 km^2 with a population of about 200,000. North-south mobility is restricted because the steep slopes (greater than 15^o, MOPUT 2001) of parallel hills and valleys running northeast to southwest meant few of the important city routes were built in this direction. Public transport in Santander has historically been provided by a network of bus lines serving 97% of the municipal territory with bus stops located at less than 300 metres apart. Santander currently counts on a public bicycle service provided by a fleet of 200 bicycles distributed between 14 recently installed docking stations and with further plans for expansion. This service was conceived to be complementary to the bus service but in competition with the private car with the aim of increasing the supply of public transport and extending its coverage. 195 users were interview in the data collection. An analysis of the data collected for characterising the service users and their journeys is presented below. Firstly, balanced distribution was observed between men and women. Secondly, almost three quarters of the interviewees were under 44 years old and half of the sample is under 25. However, 13% were between 45 and 54 years old, 12% aged between 55 and 64 and 4% aged over 64. The great majority had a driving license and slightly less had a car available for their use. In spite of a high degree of none answers, the net monthly household income was found to be over 1500 Euros in most cases half of the cases, decreasing the group of people that stated an income of between 900 and 1500 Euros or less than 900. Besides, the common user of the public bike service lives in Santander. According to the collected data, a 44% of the journeys were mainly for leisure, followed by the journeys made to go home, for studies, for work and for health reasons. A little 3% had a shopping purpose and 11% were made for other reasons. The 42% of the interviewees stated a daily usage of the public bicycles, the 31% said it was in a weekly basis, the 2%, monthly and an important 25% of the interviewees answered they rarely use it. More than half of the sample stated that they had used the bike lane during their journey, 9% said they hadn't ridden on it at all, and 33% said they had used it partially (because it didn't exist on their route or they used alternative routes). After analysing the collected data, the next step was to model the perception of the quality of service. Users were asked to mark the overall quality of the system twice: at the beginning of the questionnaire (*Iv*) as well as at the end of it (*Fv*), after having rated each of the components of the public bicycle system. These two ratings lead to two models, which yield different insights on the importance of the variables on the overall valuation. An important aspect of discrete choice models is their ability to analyse possible heterogeneity in the perceptions. The heterogeneity on the perceptions may be caused by user characteristics and journey restrictions. These factors are represented by dummy variables and form interactions between them and the ratings by a simple multiplication. As a result, the explicative variables have been introduced either as the ratings given by users or as the interactions already mentioned.

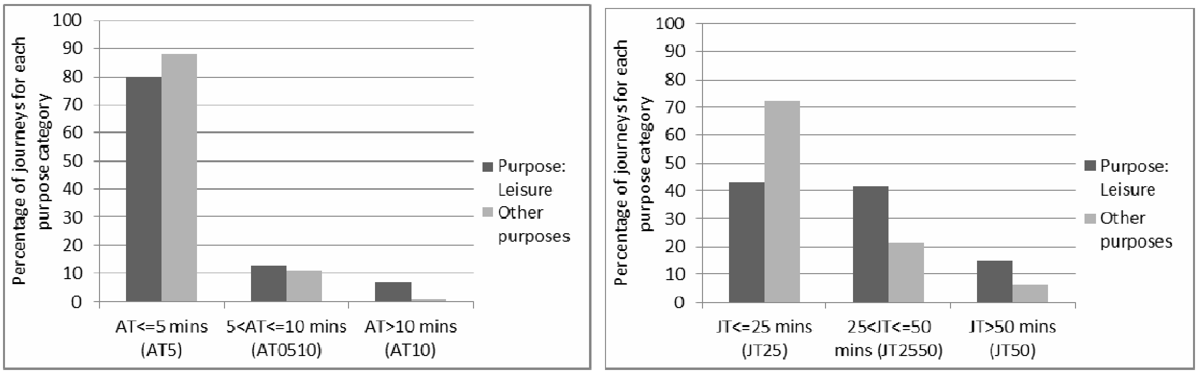

Fig. 1. (a)Percentage of journeys corresponding to each journey purpose category based on the access time (*AT*) categorization, (b) Percentage of journeys corresponding to each journey purpose category based on the journey time (*JT*) categorization

Table 1. (a) Ordered Probit Model for estimating initial perceived quality (*Iv*); (b) Ordered Probit Model for estimating final perceived quality (*Fv*)

Initial Valuation of perceived quality (Iv)		
Attribute	Coefficient	t-ratio
Constant	-0.55	-1.14
VAT	0.22	1.62
VCOST	0.87	4.83
VDIS	0.64	4.86
VBICQ	0.24	1.63
VPS	0.28	2.13
VJS	0.32	2.28
G·VCOST	-0.20	-2.40
Y·VCOST	-0.20	-2.26
ESPP·VAT	0.36	2.82
ESPP·VJS	-0.32	-2.27
DAY·VDIS	-0.64	-4.87
DAY·VPS	0.88	4.24
AT5·VCOST	-0.47	-3.29
JT25·VBICQ	0.55	3.78
Threshold parameters		
μ_1	1.30	4.79
μ_2	4.54	12.27
Log likelihood function	-110.6062	

Final Valuation of perceived quality (Fv)		
Attribute	Coefficient	t-ratio
Constant	-1.64	-2.98
VAT	0.65	4.06
VDIS	0.46	2.99
VBICQ	0.57	3.37
VPS	0.43	2.94
VJS	1.43	5.98
VINF	0.92	5.29
G·VINF	-0.28	-2.35
Y·VJS	-0.73	-4.17
M·VINF	-0.64	-4.35
ESPP·VJS	-0.70	-3.87
DAY·VDIS	-0.46	-2.99
DAY·VPS	0.65	2.81
AT10·VAT	1.53	3.64
JT2550·VAT	-0.39	-3.21
Threshold parameters		
μ_1	2.03	4.73
μ_2	6.66	9.62
Log likelihood function	-78.36520	

The perceived length of time to access the docking station as well as the perceived journey time and fee were introduced at the start of the interview resulted non-significant. Given the great variability between these data, each of the three variables was subdivided into three dummy variables representing different ranges of value (Fig. 1). Access time (*AT*) and journey time (*JT*) have been consequently divided into categories based on their values and the journey purpose, as it is justified by Fig. 1. This method provides greater precision in the characterisation of the journeys being made and helps explain the heterogeneity on opinions due to these perceived times. In the case of the cost, the three categories correspond to the three subscription modes that are currently available: daily, weekly and annual. After preparing the variables, numerous models have been calibrated attending to the significance of the parameters, the interpretation of them, and the model fit. The results of the model estimations of user perceived quality in the public bicycle service are presented below. Table 1(a) shows the results of the initial estimation of perceived quality stated at the start of the interview and Table 1(b) shows the final perceived quality, taken after the users were asked to consider each of the service attributes.

Nomenclature

Iv	Initial valuation of service quality
VAT	Valuation of time to access the system
VCOST	Valuation of the cost
VDIS	Valuation of the distribution of bicycle docking stations
VPS	Valuation of the payment system
VBICQ	Valuation of the bicycle quality
VJS	Valuation of journey safety
VINF	Valuation of the available information about the service
Fv	Final valuation of service quality
G	gender: 1=Woman; 0=Man
Y	Age: young (<35 years): 1=Yes; 0=No
M	Age: middle (35-54 years): 1=Yes; 0=No
ESPP	Specific purpose for journey: studies/work/health/shopping/others: 1=Yes; 0=No
DAY	Day ticket: 1=yes; 0=No

4. Discussion about the models

An initial analysis and comparison of the estimated models shows the influence of the valuation of the cost (*VCOST*) in the first model (Table 1(a)) but not in the second (Table 1(b)), while, on the contrary, the valuation placed on the available information about the service (*VINF*) only has an influence in the final model. In other words, the perception of the fee only influences the service quality valuation at the beginning but show no influence after they have rated each characteristic of the system. On the contrary, some characteristics of the service are not taken into account in the initial perception of overall quality but the valuation of each of them produces an increase on the influence of some of them when scoring the quality of service at the end of the interview (Fv). This exercise of rating each system attribute leads to both differences on the perceptions and the weight placed on them at the time of giving an overall score to the service (*Iv* and *Fv*). Such is the case that the most important variable in the first model is the valuation given to the fee (*VCOST*), which loses its influence in the second model, followed by the distribution of the docking stations (*VDIS*). In contrast, in the final perception of the overall quality, the most weighted aspects are the journey safety (*VJS*) and the information about the service (*VINF*), showing no influence in the first model.

Table 2. Partial effects of the model estimating final perceived quality

Variables	Y=00 Very bad/Bad	Y=01 Not good nor bad	Y=02 Good	Y=03 Very good
VAT	0	-0.0026	-0.0689	0.0715
VDIS	0	-0.0019	-0.0494	0.0513
VBICQ	0	-0.0023	-0.0608	0.0631
VPS	0	-0.0017	-0.0462	0.048
VJS	0	-0.0058	-0.1523	0.1581
VINF	0	-0.0037	-0.0978	0.1015
G·VINF	0	0.0011	0.0298	-0.031
Y·VSV	0	0.0029	0.0774	-0.0803
M·VINF	0	0.0026	0.0681	-0.0707
ESPP·VJS	0	0.0087	0.0357	-0.0444
DAY·VDIS	0	0.0019	0.0494	-0.0513
DAY·VPS	0	-0.0026	-0.069	0.0716
AT10·VAT	0	-0.0062	-0.1629	0.169
JT2550·VAT	0	0.0016	0.0411	-0.0427

The heterogeneity in the perception of quality in the bicycle hire service has its origins in causes such as gender, age, purpose of the journey, type of ticket acquired and access or journey time. In this sense, it should be highlighted the added weight that in the first model users with a day-ticket (*DAY*) place on the payment system (*VPS*) and that users making a short journey of less than 25 minutes (*JT25*) place on the quality of the bicycle itself (*VBICQ*) (Table 1(a)). As Figure 1 showed, it is probably related to a journey made by a purpose other than leisure. Furthermore, those users travelling for a specific purpose (*ESPP*) place more importance than other users on access time to the system (*VAT*). The second model, however, highlights the interaction between perceiving an access time greater than 10 minutes (*AT10*) and the importance given to that aspect when evaluating the overall quality of the service, which increases greatly compared to the other users (Table 1(b)). Similarly to the findings of the first model, the second model finds that the users who pay for a day-ticket place greater importance on the payment system.

As indicated in the methodology, the true influence of each variable on the overall perception of quality is interpreted through the partial effects. The best fit is obtained from the second model indicating it better represents the process of evaluating the overall service quality as a function of its defining characteristics. This is the reason for presenting the partial effects corresponding to the final model (Table 2). The partial effects represent the percentage increase (positive sign) or decrease (negative sign) in the probability of choosing each score for the final overall quality rating (*Fv*) as a result of a unit improvement in the value of each explanatory variable.

The factor with greatest impact on increasing the probability of getting the best evaluation of overall quality is the value placed on journey safety (*VJS*), as indicated in the above discussion about the calibrated models. The partial effect corresponding to this variable quantifies an increase of 15.81% in the mentioned probability as a response to the unit improvement in the perception of the safety. Similarly, an improvement of one in the valuation scale of the available information about the service causes an increase of 10.15% in the probability of giving the maximum score to the overall quality of service.

The heterogeneities expressed by the model from the investigated interactions are a result of the analysis of the accumulated value of the partial effects of the variable represented by itself and from the interaction. Therefore, a unit improvement in the valuation of access time to the system provides a 24.05% greater probability that the users who currently perceive an access time of greater than 10 minutes will score the service as "Very good". This increase in probability is the sum of the partial effects relative to *VAT* for the population of users (7.15%) and for the group of users mentioned (16.9%). If improvements are made to the perception of the payment system, the probability that users with a day subscription would value the quality of the system with the highest score increases by a total of 11.96%, being the sum of 4.8% for the population of users and 7.16% for the stated group of users.

The rest of the interactions causing systematic variations in user perception result in a lower probability (compared with the general user population), for the represented user categories, of giving the score "Very good" to the overall quality of service. The corresponding reductions are the consequence of the fact that users represented in these interactions place less importance than the rest on the corresponding variables and, therefore, the accumulated value of the partial effects is lower (due to the negative sign of the partial effect associated with the interaction) for them than for the general population of users. The improvement made to the available information will have a 3.1% lower impact on women and a 7.07% lower impact on users aged between 35 and 54. If the same user has both these characteristics, in spite of improving this variable, the impact will be null given that these two characteristics explain that the weight of the *VINF* variable is null, which is also observed from the parameters calibrated by the model (Table 1(b)). Another of the represented interactions is the lower impact an improvement in safety has on younger users' (under 34 years old) perception of quality compared with the rest of the users. A specific use of the service for a journey made for study, work, health, shopping or other purposes also results in a lower impact. The same occurs with users who take out a day-ticket if improvements are made in the distribution of the docking stations, since it is usually unknown to them given the sporadic nature of their usage. The final interaction relates a journey lasting between 25 and 50 minutes with the value of access time. As Fig. 1 shows, the percentage of journeys made within this range is double for the purpose of leisure than for the other purposes. In these circumstances it would be expected that access to the system would not be as important as for the other users, demonstrated by the negative sign of the parameter associated with this interaction in the calibrated model and the corresponding partial effect.

5. Conclusions

The efficiency of managing the public bike service and the success of its integration into the global supply of public transport requires an in-depth analysis of its characteristics and the perception that users have of each attribute. This article proposes a methodology for modelling the perceived quality of this service in order to identify the influential variables and their relevance in the overall valuation.

This research verifies the different perception that users have of the service quality before and after having rated all its components. In the case studied here, this reflection causes a reduction in the importance placed on tangible aspects such as the fee and the distribution of the bicycle docking stations, resulting in increased importance being placed on safety and available information about the service, this latter being of null importance when the initial valuation of quality was made. Therefore, the greatest impact on public bike users' perceived quality will be achieved by improving these two factors: safety and information.

The profound analysis of heterogeneity confirms that users of the bike sharing service perceive quality significantly differently depending both on journey restrictions such as access time, journey time or the type of ticket purchased, as well as on socio-economic characteristics such as gender and age. Referring to the systematic variation in the perceptions, the greatest impact on perceived quality would be generated by making improvements in access time and, more precisely, for those users whose current access times are greater than 10 minutes.

Many factors influence the perception of quality in a public bicycle service. However, the access and journey times, along with the cost, don't show any influence by themselves on the perception of quality but they do induce heterogeneity at the time of rating various service attributes.

The methodology presented in this article provides, important insights for improving knowledge about user perception of a public bike service currently being provided and the aspects on which they place greater importance. Its application is suitable to any public bicycle system and gives the design guidelines for making improvements to the service by knowing the impact they would have on the overall perception of quality.

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