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A methodology for modeling and identifying users satisfaction issues in public transport systems based on users surveys

J. M. Del Castillo*, Francisco G. Benitez

Transportation Engineering, Faculty of Engineering, University of Seville, Seville E-41092, Spain

Abstract

The quality of public transport can be measured directly through user surveys by rating different aspects of the service, such as punctuality, network coverage, connectivity of the lines, frequency of service, etc.. In addition to these ratings, the survey may ask users to rate the overall quality of service. This approach aims to identify the aspects that mostly influence the perception of overall quality of service. This paper presents a methodology to identify and quantify the relationship between the ratings given to the overall satisfaction and those given to specific aspects of the service or specific ratings. The methodology is based on the use of three different models: models based on averages, a model based on a multivariate discrete distribution and a generalized linear model. The comparison of the results given by these models allows to identify and quantify the most relevant and influential aspects regarding user satisfaction. The final result is a model of the overall satisfaction index in terms on the most influential specific aspects.

Keywords: public transport, user satisfaction, quality survey, weighted mean, multivariate discrete distribution, generalized linear model.

1. Introduction

Most public transport companies are becoming more aware of the importance of user satisfaction with the service given. Therefore, the evaluation of the most significant aspects in relation to user satisfaction is a priority. User satisfaction is defined as "the overall level of compliance with user expectations, measured as a percentage of really met expectations" (Tyrinopoulos and Antoniou, 2008). The level of satisfaction or "overall satisfaction" is therefore an aggregate measure of user satisfaction with various aspects of the service, or "specific satisfactions".

* Corresponding author. Tel.: +34-95-4486080; fax: +34-95-4487316.
E-mail address: delcastillo@us.es

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The contribution of this paper is twofold. Firstly several models are proposed to estimate the overall satisfaction from the specific satisfactions. Specifically, we propose a mean-based models, one model based on a multivariate discrete distribution and finally a generalized linear model. These three models are fitted to a sample obtained from users of the public bus company in Bilbao (Spain). The use of these models in the context of transport is novel and original. Second, the joint analysis of the quantitative results given for each of the aspects, allows the robust identification of the most influential aspects on the overall satisfaction.

Recent work in the field of surveys to public buses users are those of Stradling et al. (2007) and Fellesson and Friman (2008). The results of these studies show that the aspects of service that contribute most to the overall satisfaction are the appropriateness of the timing, frequency and reliability of service, the information provided to the user and other aspects of lesser interest. Other works on the same line are those of Eboli and Mazzulla (2007, 2009), Krizek and El-Geneidy (2007), Agarwal (2008), Budiono (2009), Wu et al. (2009), Ji and Gao (2010), and Dell'Olio et al. (2010).

The problem of finding an overall measure of a series of observations, measurements or results appears in many fields of science and engineering. Thus, there are many different methods to address this problem. In principle, these methods can be divided into two types, depending on whether certain statistical assumptions are made on the observations or not. Methods that are not derived from statistical hypotheses are very diverse, ranging from methods based on the use of aggregation functions, or operators to methods based on fuzzy logic or neural networks. Methods based on statistical hypotheses are also relatively diverse. Most works employ structural equations and regression modeling in order to obtain an overall satisfaction index.

As mentioned above, this paper introduces three models to predict the overall satisfaction from the specific satisfactions. The first model is a model based on average that is easy and intuitive. For this reason, this model is used to "benchmark" to compare the results of the other two models, which are models based on probability distributions. These two models, the one based on a discrete distribution and the generalized linear model have the advantage of providing not only an estimate of the overall satisfaction but also its distribution. This fact is particularly interesting since it allows to obtain confidence intervals for this index.

2. Brief description of the survey

In May 2010 a survey was conducted between 1508 users of the public bus company in the spanish city of Bilbao. The survey was carried out on weekdays through interviews with randomly selected passengers. The survey included most of the lines of the bus network. The questionnaire contained 35 questions related to various aspects of the service, such as frequency, travel time, punctuality, prices, information, cleanliness, staff performance, comfort and safety. Each respondent was asked to rate from 0 to 10 the level of satisfaction with each of the 35 previous aspects. The resulting scores are called in the following specific satisfactions (SS) and are grouped in 8 categories or blocks. The list of blocks and aspects or corresponding items are given in Table 1. Additionally, respondents also rated on a scale of 0 to 10 their overall or global satisfaction with the service (GS).

3. Models based on means

For all sample observations, it was found that the GS was between the minimum and maximum scores given to the SS. This is somewhat indicative of the user responses are consistent among themselves and make a model based on a mean be especially attractive to relate the GS with the SSs. Specifically and according to Bullen (2003), a mean of a set of real numbers is a function that satisfies the following property:

Table 1. List of items classificated in blocks.

Block	Item
1. CONNECTIVITY	1. Connection to lines of the same operator
	2. Connection to lines of other operators
	3. Line diversity (number of lines of the transit network)
2. ACCESSIBILITY	4. Accessibility of the bus network (number of bus stops)
	5. Reduced mobility users' accessibility
	6. Adequacy of the most used bus stop location
3. INFORMATION	7. Service information availability
	8. Availability of timetables and line plans
	9. Line information explicitness
	10. Information panels on terminals and bus stops
	11. Information panel on next stop
	12. Information on passes and tariffs
4. TIME SATISFACTION	13. Bus punctuality
	14. Service frequency
	15. Trip duration
	16. Line reliability
	17. Service time window
5. USER ATTENDANCE	18. Driver kindness
	19. Staff kindness
6. COMFORT	20. Physical state of vehicles (quality, conservation, new/old)
	21. Bus cleanliness
	22. Bus comfort
	23. Bus illumination
	24. Bus temperature adequacy
	25. Average user volume (occupancy)
	26. Professionality/caution/driver skillfulness
	27. Bus stop coziness (weather conditions)
	28. Bus stop conservation and cleanliness
	29. Bus stop illumination
	30. Adequate visual arrival of buses at bus stops
7. SECURITY/SAFETY	31. Bus safety (vehicles)
	32. Security on buses
	33. Bus stop safety
8. ENVIRONMENTAL IMPACT	34. Noise
	35. Bus contribution to traffic fluidity

$$\min(x_1, x_2 ... x_d) \leq M(x_1, x_2 ... x_d) \leq \max(x_1, x_2 ... x_d)$$

A simple and flexible model is that given by the weighted power mean (WPM):

$$M(x_1, x_2 ... x_d) = \left(\sum_{k=1}^{d} w_k x_k^{\beta} \right)^{1/\beta}$$

Where the weights w_k sum one. In principle the exponent β may be positive or negative. An attractive property of the model is the fact that it contains the following models as limit cases:

$$\lim_{\beta \to 0} M(x_1, x_2 ... x_d) = \prod_{k=1}^{d} x_k^{w_k}$$
$$\lim_{\beta \to \infty} M(x_1, x_2 ... x_d) = \max(x_1, x_2 ... x_d)$$
$$\lim_{\beta \to -\infty} M(x_1, x_2 ... x_d) = \min(x_1, x_2 ... x_d)$$

Additionally, it reduces to the weighted arithmetic mean (WAM) if β=1. The survey consists of 35 items to be rated, that is, d=35, which implies that the WPM model has a total number of 36 parameters (the weights w_k and the exponent β) and a linear constraint for 35 parameters. The estimation of the parameters was carried out by minimizing the average absolute error given by

$$\varepsilon_{abs} = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_{abs_i} = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|$$

In the above expression y_i is the rating given by the individual i to the global satisfaction (GS) and the forecasted global satisfaction of that individual is:

$$\hat{y}_i = \left(\sum_{k=1}^{d} w_k x_{ik}^{\beta} \right)^{1/\beta}$$

where x_{ik} is the rating given to item k by the individual i. The error is minimized for a value of $\beta = 1.0122$, that is, with a model closed to the weighted arithmetic mean. Finally, the value of the error is ε_{abs}= 0.85359 with the WPM and ε_{abs}= 0.85625 for the WAM. Table 2 shows the weights (in %) for each service aspect given by the weighted power mean (WPM) and by the arithmetic power mean (WAM). The item numbering is that used in Table 1 and the items have been arranged in decreasing order of their weights. It can be seen that the value of the weights and the order are almost the same with both models.

4. A discrete distribution for modeling the ratings

This section presents a radically different way of predicting the GS from the SSs. In this new approach, the sample ratings of the survey are modeled with a multivariate discrete distribution. Specifically, if the sample consists of the specific and the overall ratings from the individual i, they are considered as an observation of the d+1 dimensional random variable $\mathbf{n}=(y, x_1, x_2,... x_d)$. The goal of this new approach is finding an expression of the probability that an individual rates the survey items in a given way. Namely, the probability that the individual i

gives a rating of y_i, x_{i1}, x_{i2},... x_{id} to the global and the specific satisfactions will be:

$$f(y_i, x_{i1}, x_{i2}..., x_{id}) = \mathrm{Prob}(Y = y_i, X_1 = x_{i1}, X_2 = x_{i2}..., X_d = x_{id})$$

Table 2. Weights for the items given by the WPM and WAM models, listed in decreasing order.

Index of item	Weights ($W_k \times 100$)		Cumulative weight (%) for WPM model
	WPM model $\beta = 1.0122$	WAM model $\beta = 1$	
16	17.0340	17.0370	17.0
6	12.2920	12.3090	29.3
23	10.2860	10.3480	39.7
13	9.9989	9.9815	49.7
2	9.6967	9.7140	59.4
14	8.0060	8.0172	67.4
3 (WPM) or 4 (WAM)	5.1693	5.1656	72.6
4 (WPM) or 3 (WAM)	5.1664	5.1317	77.7
17	4.7043	4.6899	82.4
24	4.0592	4.0158	86.4
1	3.2048	3.1920	89.6
21	3.1873	3.1761	92.8
25	2.0468	2.0311	94.8
26	1.3519	1.3795	96.2
20	1.2660	1.2759	97.5
5 (WPM) or 15 (WAM)	1.0070	1.0258	98.5
15 (WAM) or 5 (WPM)	0.9861	0.9904	99.5
7	0.5370	0.5196	100.0

Then, the prediction of any variable when the others are known is given by the conditional expectation of that variable. In particular, the prediction of the GS rating of individual *i*-th when the ratings of the known SSs will be:

$$\hat{y}_i = \mathrm{E}(Y \mid X_1 = x_{i1}, X_2 = x_{i2}..., X_d = x_{id}) = \frac{\sum_{y=0}^{10} y f(y, x_{i1}, x_{i2}..., x_{id})}{\sum_{y=0}^{10} f(y, x_{i1}, x_{i2}..., x_{id})} = m(x_{i1}, x_{i2}..., x_{id})$$

The validity of this model depends on the goodness of fit to the sample obtained by adopting a specific discrete distribution. The starting point for the choice of the distribution arises from the result proved by Becker and Utev (2002) on the analytical form of the conditional expectation of a function of one variable conditional on the remaining variables. The result is valid in certain discrete multivariate distributions that are characterized by the fact that the dependence between variables is introduced by a number of product terms. In this work, we have adopted the following expression for the discrete distribution:

$$\text{Prob}(N_1 = n_1,..., N_d = n_d) = f(n_1,...,n_d;\boldsymbol{\alpha},\boldsymbol{\theta}) = C(\boldsymbol{\alpha},\boldsymbol{\theta})\exp(-\mathbf{nAn^T})\prod_{i=1}^{d} f_i(n_i;\theta_i) \tag{1}$$

where $\mathbf{n}$=(n_1, n_2,... n_d) is the d-dimensional random variable and $f_i(n_i;\theta_i)$ is a binomial distribution with parameters m and θ_i whose expression is:

$$f_i(n_i;\theta_i) = \binom{m}{n_i}\theta_i^{n_i}(1-\theta_i)^{m-n_i}$$

That is, the variables can take integer values from 0 to m. On the other hand, $\mathbf{A}$ is a symmetric matrix whose diagonal elements and zero, ie. α_{ii} = 0. The factor C depends on all parameters and a normalization factor is necessary so that the sum of all the possible values of the probability function is equal to one. It is important to note that if all the elements α_{ij} of the matrix are zero, then the distribution is the product of binomial distributions and therefore the random variables are independent and binomial. In this case, the conditional expectation of a variable on the other would be not function of those and the prediction would be meaningless.

In what folllows, the symbol $\mathbf{n}_{-i}$ will be used for the d-1 dimensional random variable resulting from eliminating the variable i, that is: $\mathbf{n}_{-i}$ = (n_1, n_2,... n_{i-1}, n_{i+1},... n_d). Del Castillo and Benítez (2012) shows that the conditional distribution of a variable with respect to the others is also a binomial distribution. It is therefore possible to obtain the expression of the conditional expectation, that turns out to be:

$$\text{E}(N_i \mid \mathbf{n}_{-i}) = \frac{m}{1+\exp\left[-\pi_i + \sum_{k=1}^{d}\alpha_{ik}n_k\right]} \tag{2}$$

where

$$\pi_i = \log\left(\frac{\theta_i}{1-\theta_i}\right)$$

In addition to the conditional expectation as a prediction of the value of a variable when the rest are known, it is also of great interest to predict this value as the mode of the conditional distribution. In this case, and recalling that the conditional distribution remains a binomial distribution we have:

$$\text{Mode}(N_i \mid \mathbf{n}_{-i}) = \left\lfloor (m+1)\tilde{\theta}_i \right\rfloor = \left\lfloor (m+1) \Big/ \left(1+\exp\left[-\pi_i + \sum_{k=1}^{d}\alpha_{ik}n_k\right]\right)\right\rfloor \tag{3}$$

where $\lfloor k \rfloor$ is the closest integer to k being smaller than k.

The distribution (1) has never been used before in the field of transport. Most applications of (1) are limited to binary variables, or in other words, in cases where m = 1 and the variables take only the values 0 or 1. In such cases, the distribution has been called quadratic binary distribution. This distribution has been used by Cox and Wermuth (2002) in studies in the area of social sciences. Another important use of the distribution in the binary case is for the random graph modeling (Van Duijn et al., 2009).

The choice of the distribution (1) is very natural, since it is an exponential family distribution whose sufficient statistics are the sample moments of N_i and N_iN_j. The distribution has a clear interpretation in terms of information content, in the sense that it is the discrete distribution of maximum entropy when the only known sample statistics are the means and cross moments.

Fitting the distribution using the maximum likelihood method has the disadvantage that the normalization constant of the distribution is not a closed analytical expression and its numerical evaluation would be unacceptable in terms of computing time. To avoid this problem and because of the particular form of the distribution, the parameters can be estimated using maximum pseudolikelihood estimators. This concept was introduced by Besag (1974) and has been used to estimate the parameters of the distributions where the numerical evaluation of the normalization factor is not feasible. The pseudolikelihood is simply the sum of the likelihood of the conditional distributions. Del Castillo and Benitez (2012) explains how the expression of the pseudolikelihood is obtained and it is shown that is a concave function in the parameters to be estimated, π_i. and α_{ik}. This means that the optimal value of these parameters is unique. Section 6 presents the results obtained with this model.

5. A generalized linear model

In the previous section we have proposed a model for the survey based on a discrete distribution whose conditional distributions are binomial. As we are only interested in predicting the overall satisfaction index and since the index takes values between 0 and 10, an appropriate model for this type of variable is a generalized linear model where the dependent variable follows a binomial distribution whose parameter varies linearly with the independent variables. This is the most common form of a binomial generalized linear model (Hardin and Hilbe, 2007), in which the dependent variable, which is the overall satisfaction rating, follows a binomial distribution of parameters m and θ whose "log odds ratio" or logit depends on the independent variables as follows:

$$\log\left(\frac{\theta}{1-\theta}\right) = \pi = \beta_0 + \sum_{k=1}^{q} \beta_k X_k = \boldsymbol{\beta}\mathbf{X}$$

where the coefficients β_k, k= 0,...q are estimated from the sample. The global satisfaction index can be predicted according to the mean of the distribution and in this case we have:

$$\hat{Y}_i = \mathrm{E}(Y_i \mid \mathbf{X}_i) = \frac{m}{1+e^{-\pi_i}} = \frac{m}{1+\exp\left[-\beta_0 - \sum_{k=1}^{q} \beta_k X_{jk}\right]} \tag{4}$$

If the prediction of the global satisfaction index is made according to the mode of the distribution, the following expression will be used:

$$\hat{Y}_i = \mathrm{Mode}(Y_i \mid \mathbf{X}_i) = \left\lfloor \frac{m+1}{1+e^{-\pi_i}} \right\rfloor = \left\lfloor (m+1) \middle/ \left(1+\exp\left[\beta_0 + \sum_{k=1}^{q} \beta_k X_{jk}\right]\right) \right\rfloor \tag{5}$$

6. Analysis of the results

In estimating the model based on the distribution (1) the number of parameters to estimate, if the full sample is chosen, would be equal to 36x35/2 = 666. To reduce this number so that it is substantially less than the sample size, two models with less parameters have been considered. These are the models resulting from taking from the whole sample only the 4 and 8 most relevant items, respectively. The order of relevance of the items is that given by the weighted power mean model. These two models based on the distribution (1) are called MD4 and MD8 and are specifically:

- Model MD4: model adjusted to the sample containing only the 4 most relevant aspects, that are those of items 16, 6, 23 y 13 (see Table 2).
- Model MD8: model adjusted to the sample containing only the 8 most relevant aspects, that are those of items 16, 6, 23, 13, 2, 14, 4 y 3 (see Table 2).

Likewise, the generalized linear model was adjusted considering also the sample of 4 and 8 most relevant items, respectively. These models are called GLM4 and GLM8. The model with the full sample of 35 items has also been adjusted and this model is called GLM35. This model has 36 parameters and it is interesting because it may show the improvement of the prediction of overall satisfaction index when one considers all the sample information.

Table 3 shows the errors given by the above models. The error in the second column is the absolute mean error whose expression is:

$$\varepsilon_{abs,mean} = \frac{1}{n}\sum_{j=1}^{n}\left|Y_j - \mathrm{E}(Y_j \mid \mathbf{X_j})\right|$$

For the models MD4 and MD8, the condicional expectation is given by (2), whereas for the generalizaed linear models (GLM4, GLM8 and GLM35) is given by (4). The third column of Table 3 shows the errors obtained by using the mode of the conditional distribution for the prediction of the overall satisfaction rating. This error is calculated according to the expression:

$$\varepsilon_{abs,mode} = \frac{1}{n}\sum_{j=1}^{n}\left|Y_j - \mathrm{Mode}(Y_j \mid \mathbf{X_j})\right|$$

For models MD4 and MD8 the mode of the conditional distribution is obtained from (3) and for the generalized linear models GLM4, GLM8 GLM35 the mode is obtained from (5). As it can be deduced by comparing the values of the second and third columns of Table 3, errors given by the conditional mode are slightly smaller. In addition, the fourth column of Table 3 shows the percentage of correct predictions of the GS with the mode of the conditional distribution. This is the percentage of observations whose rating given to the GS matches the mode of the conditional distribution. The percentage of correct predictions increases slightly as more variables are included in the model.

By comparing the errors derived by the models GLM8 and GLM4 with those generated by models MD4 and MD8, we see that the errors are slightly higher in the last two for the same number of variables. GLM35 model considers all the elements of the survey on the distribution of the rating of the GS and requires the estimation of 36 parameters. We can compare the errors given by the MD and GLM models with that given by the weighted power mean model and by the weighted arithmetic mean, which are also given in Table 3. Note that this error is comparable to those produced by the model GLM35 with the conditional mean and the conditional mode and to that given by the GLM8 with the conditional mode.

The errors given by the other models are slightly higher, due to the fact that these models consider fewer items. However, these fact does not make these models less useful than the WPM model. Indeed, the advantage of the generalized linear model and the model based on the distribution is the possibility of obtaining not only the estimate of the GS rating, but also its entire distribution, and particularly confidence intervals for this estimate. Resampling methods could allow the construction of confidence intervals for the GS rating given by the power weighted mean model, but at a higher computational cost. Finally, another remarkable aspect of the model based on the distribution and of the generalized linear model is the fact that, for each individual in the sample, the predicted values of the GS with both types of predictors, the conditional mean and mode are always located between the minimum and maximum values of the rating given by the individual to the suvey items. In other words, the mean and the conditional mode of the distribution behave as a mean in the sense of the models introduced in Section 3.

Table 3. Results given by the distribution and by the linear generalized model

Model	Mean absolute error with mean: $\varepsilon_{abs,mean}$	Mean absolute error with mode: $\varepsilon_{abs,mode}$	Right predictions with mode (%)
MD4: Distribution of GS rating + 4 most relevant items	0.90728	0.89589	35.41
MD8: Distribution of GS rating + 8 most relevant items	0.88704	0.87997	37.20
GLM4: Generalized linear model with 4 most relevant items	0.89783	0.87997	37.00
GLM8: Generalized linear model with 4 most relevant items	0.86495	0.85743	37.40
GLM35: Generalized linear model with all items	0.85767	0.84947	37.20
WPM (weighted power mean)	0.85359	--	--
WAM (weighted arithmetic mean)	0.85625	--	--

7. Selection of the most relevant service aspects

The identification of the most important service aspects for the users is a key issue for service improvement. The conditional mean of the distribution coefficient decreases with models based on MD4 and MD8 distribution (1). The aspects that users perceive as most important are those whose coefficients have a lower value in these models. The opposite holds for the generalized linear model, as the mean and the conditional mode increase with α_{ij}. Table 4 shows the values of the coefficients obtained after fitting the models MD4, MD8, GLM4, GLM8 and GLM35. The first column shows the number of the survey item as numbered in Table 1. The p-values of the coefficients in the models GLM4, GLM8 and GLM35 that are greater than 0.01 are given in parentheses in the table. In particular, item 4 in the GLM8 model is not significant and neither are the items 3, 4 and 17 for the full model GLM35. Interestingly, in the full model, item 23 (bus illumination) is not as significant as in the model with 8 variables, since it has a lower coefficient and a high value of p. Finally, the model allows the identification GLM35 item 17 (service time window) as significant. However, this item has a coefficient with a relatively low value. Table 4 lists only some of the values of the coefficients α_{ij}. for the GLM35 model. Those not shown have a coefficient whose value is negligible.

One can clearly deduce that the most important aspect is that corresponding item 16 (line reliability), which appears in the first position on all models except MD4, in which it is in second position. Another important aspect according to the models GLM8 and GLM4 would be item 23 (bus illumination), which appears in the third and second place respectively. However, this aspect is not very relevant in the MD8 and GLM35 models. Moreover, item 6 (adequacy of the most used bus stop location) is very relevant and is the second / third most important in models based on the distribution. Moreover, its coefficient attains a significant value for the generalized models.

Finally, items 13 (bus punctuality), 2 (connection to lines of other companies) and 14 (service frequency) can also be considered relevant, since their coefficients have values significantly higher in both types of models. Service frequency is a bit more relevant than the connection to other lines. Aspects or items 16, 6, 13, 2 and 14 are clearly the most important in all models, and in general terms, the first is about twice as important as the others. Finally, items 17 (service time window) and 3 (line diversity) also have some relevance according to the models GLM35, GLM8 and MD8.

Table 4. Coefficient values given by the distribution and by the generalized linear model

Item number / Model	MD4	GLM4	MD8	GLM8	GLM35
16	-0.09677	0.13228	-0.15677	0.09882	0.08620
6	-0.08387	0.07566	-0.09176	0.04987	0.04859
23	-0.04474	0.08491	-0.00280	0.06734	0.04516 (0.03276)
13	-0.14651	0.10073	-0.02661	0.05463	0.04422
2			-0.04487	0.05742	0.04740
14			-0.06726	0.06583	0.05838
4			0.04529	0.02537 (0.08610)	0.02187 (0.16100)
3			-0.05604	0.03200 (0.01280)	0.01864 (0.16530)
17					0.02861 (0.02730)

In summary, the five most important aspects are: line reliability, bus stop location adequacy, bus illumination, bus punctuality, connections to lines of other operators and service frequency. It is hardly a surprise that the user satisfaction with the bus service is concentrated on a few aspects that have a great impact on it. By comparing the weight that each model gives to the different aspects or items, we can eliminate those aspects whose weight is not homogeneous in all models. This approach ensures a robust selection of the most significant aspects. In particular, the comparison between the different models allows to discard the item 23 (bus illumination) as relevant.

8. Conclusions

This paper discussed a methodology that can be used to predict the overall satisfaction index of a public transport service user in terms of the satisfaction with various aspects of the service. The most important utility of having a predictive model of the overall satisfaction index is the possibility of identifying those aspects of the service that have a greater influence on the user satisfaction. In addition, the model quantifies this importance and this information can be used by the transit service operator to focus the service improvement on the most relevant aspects for the users.

The methodology presented in this work is based on three different models: a model based on means, a model based on a statistical distribution and finally a generalized linear model. The advantage of the estimation of these three models is that it allows the robust identification of the service aspects that mostly contribute to the overall satisfaction. The robustness is achieved by comparing the results given by the three models and considering only those aspects that are clearly identified as significant by most of the models. The methodology has been applied to a sample obtained from users of the public bus company in Bilbao and has identified five aspects are very relevant from a set of 35 different service aspects.

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