Transit service quality analysis using cluster analysis and decision trees: A step forward to personalized marketing in public transportation

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ABSTRACT

A transit service quality study based on cluster analysis was performed to extract detailed customer profiles sharing similar appraisals about the service. This made it possible to detect specific requirements and needs regarding the quality of service and personalize the marketing strategy. Data from various Customer Satisfaction Surveys conducted by the Transport Consortium of Granada (Spain) were analyzed to distinguish these groups; a decision tree methodology was used to identify the most important service quality attributes influencing passengers overall evaluation. Cluster analysis determined four groups of passengers. Comparisons using decision trees among the overall sample of users and the different groups of passengers identified by the cluster analysis led to the discovery of differences in the key attributes involved in perceived quality.

1. INTRODUCTION

The assessment and evaluation of quality in public transport services seems to be a relatively new undertaking, as almost all studies found addressing this topic were published within the last 15 years (Redman et al., 2013). Several governments promote the use of public transportation and strive to improve its quality in order to make it more appealing (Paquette et al., 2012). Moreover, improvements in public transport services may influence users' satisfaction with the travel conditions and, as a consequence, the individuals' evaluations of life on the whole (Ettema et al., 2011). Such "transport happiness" as part of the individual's well-being should be a target for policy makers (Duarte et al., 2010). Performance measures have become an essential tool for transit agencies aiming to establish strategic goals for the continuous improvement of the services delivered (Eboli and Mazzulla, 2012).

Depending on the viewpoint adopted for analyzing service quality (service managers' perspective vs. passengers' perspective), significant discrepancies may exist about the level of quality provided and what is really important for service. Rietveld (2005) stated that public transport suppliers tend to overestimate the quality of service provided when compared to customer evaluations; Parkan (2002) claims that when service quality evaluation is conducted by public transport suppliers, the list of attributes held to be important differs from the key factors considered by users.

Because service suppliers strive to provide a user-based quality service, it seems more appropriate to analyze service quality based on passengers' opinions. Indeed, users are the ones who suffer from the poor quality of service or who are delighted with high levels of performance. Customer satisfaction surveys are a means of collecting and processing these opinions in order to design adequate interventions and strategies.

The main problem to be faced along the way is the subjective nature of such measurements, offering fuzzy and heterogeneous passenger assessments. Moreover, passengers have different perceptions about each service attribute due to their specific needs and preferences towards the service. This reduce the reliability of service quality evaluation in terms of the influence each attribute exerts on the overall service quality (attributes' importance) and the level of quality of these attributes. Discrete choice models with random parameters are an option for capturing this heterogeneity (Hensher et al., 2010), allowing to consider the variation of users' perceptions in the parameters of the model. Likewise, stratifying the sample of users on segments of passengers with more uniform opinions about the service represents another option for solving the heterogeneity limitation.

Some studies stratify survey samples in order to reduce the heterogeneity and propose specific models (e.g., Dell'Olio et al., 2010; De Oña et al., 2014a). Authors Abou Zeid and Ben-Akiva (2010) demonstrated that people report different levels of travel happiness under routine and non-routine conditions, through an experiment requiring habitual car drivers to switch temporarily to public transportation. Studies with stratified sampling tend to be based on the social and demographic characteristics of the passengers (i.e., models for women, for the elderly, according to income level), or their travel habits (i.e., type of day of the journey, time of the day, frequency of use). That is, the segmentation is based on methodological decisions or the wish to study a specific problem. Expert knowledge can lead to a workable segmentation of the data, yet it does not guarantee that each segment consists of a homogenous group. Therefore, transit service quality analysis could benefit from a technique to aid the process of segmentation, such as Cluster Analysis (CA). CA is a data mining technique used to separate data elements into groups so that the homogeneity of elements within the clusters and the heterogeneity between clusters are maximized (Hair et al., 1998).

CA has been applied to other fields of transport engineering with satisfactory results (Karlaftis and Tarko, 1998; Outwater et al., 2003; Ma and Kockelman, 2006; Depaire et al., 2008; De Oña et al., 2013b). Depaire et al. (2008) and De Oña et al. (2013) obtained different segments of traffic accidents using Latent Class Cluster. However, as far as the authors know, CA has not been used to establish homogeneous groups of users with regards to service quality evaluation in a public transport setting. Then, in this paper CA is applied to deal with passengers' heterogeneity, given that it stratifies the sample of passengers into groups with common characteristics, and who would have more homogeneous perceptions about the service. Moreover, CA not only helps to deal with heterogeneity as other techniques used before, such as discrete choice models with random parameters or traditional stratification, but it identifies specific passengers' profiles using the transit service, allowing to better understand passengers' behavior.

This methodology for market segmentation facilitates more personalized marketing, tailored to specific needs or desires of different groups of passengers. The notion is a familiar one in businesses today: customizing service increases customer satisfaction and loyalty (Cheung et al. 2003; Vesanen, 2007). Public transport information and marketing campaigns aim to expressly encourage public transport use (Sanjust et al., 2014). In fact, research projects INPHORMN (1998) and its successor TAPESTRY (2003) proved that using information, marketing and community education as part of an integrated transport plan can significantly increase levels of public awareness, influence public attitudes and enable people to make changes in their travel behavior (reduce car use and increase cycling, walking, car sharing and the use of public transport, etc.). Many studies show that customized information is more effective than mass communication when involving individuals and changing travel behavior (Gärling and Fujii, 2009).

The main purpose of this study is therefore to apply a cluster analysis technique to stratify the sample of users of a public transport service in the city of Granada (Spain) so as to analyze service quality in view of detailed passenger profiles. Service quality will be analyzed both with and without segmentation of passenger profiles, so that the results can be compared.

Traditionally, service quality assessment involved regression models such as logit or probit (Eboli and Mazzulla, 2008, 2010; Hensher, 2003; dell'Olio et al., 2011), structural equation models (De Oña et al., 2013a, Eboli and Mazzulla, 2007, Eboli and Mazzulla, 2012; Irfan et al., 2011), etc. However, most of these models have some limitations, because pre-defined assumptions and relations between dependent and independent variables are supposed, hence erroneous estimations of the likelihood of service quality are obtained when these assumptions are violated. To avoid such problems, service quality evaluation can be analyzed using Data Mining Techniques such as Artificial Neural Network (ANN) or Classification and Regression Tree (CART) methodologies. They resolve some limitations found in traditional models, given that they are non-parametric techniques that do not require prior probabilistic knowledge on the study phenomena. Garrido et al. (2014) used an artificial neural network approach for analyzing service quality in a metropolitan bus service, by using three different algorithms in order to find the most reliable of them. In addition, CART methodology has successfully been applied in different public transport systems by De Oña et al. (2012; 2014a; 2014b) and De Oña and de Oña (2013). CART considers conditional interactions among input data, providing useful "If-Then" rules supporting policy making, and it determines the value of the standardized importance of independent variables, which reflects the impact of such predictor variables on the model. Furthermore, CART methodology might be preferred over ANN by public transport managers because its simplicity and graphic representation of their results (De Oña et al., 2015). For this reason, in this research, service quality evaluation will be analyzed by CART methodology.

The paper is organized as follows: First, the methodology used for stratifying the sample and for evaluating service quality is presented. Second, the experimental context and data used for the analysis are described. Third, the outcomes obtained through cluster analysis and decision trees are detailed. A final section highlights the main findings and conclusions of the research.

2. METHODOLOGY

~~CA is applied in order to obtain segments of the whole sample of users, the segments representing passenger profiles. Service quality is then explored using CART methodology performed on the entire sample of users as well as particular groups of passengers identified.~~

2.1. Cluster Analysis

The main aim of Cluster Analysis (CA) is classify the data into groups (clusters) with similar characteristics, trying to maximize the similarity between in-cluster elements and the dissimilarity between inter-cluster elements (Fraley and Raftery, 1998). Then, in this paper CA is applied to deal with passengers' heterogeneity, given that it stratifies the sample of passengers into groups with common characteristics, and who would have more homogeneous perceptions about the service.

Latent Class Clustering (LCC) is a particular method affording some important advantages over other types of CA, such as K-means, Ward's method, or a single linkage method (Hair et al., 1998; Magidson and Vermunt, 2002; Vermunt and Magidson, 2005). Some of these advantages are: being able to use different types of variables (frequencies, categorical, metric variables) with no need for prior standardization that could have a bearing on the results; and providing several statistical criteria that help to decide the most appropriate number of clusters.

The formulation of the LCC is as follows: given a data sample of N cases, measured with a set of observed variables, $Y_1,\ldots,Y_j$, which are considered indicators of a latent variable X; and these variables form a Latent Class Model (LCM) with T classes. If each observed value contains a specific number of categories (Yi contains $\mathbf{I_i}$ categories, with i=1…j), then the manifest variables make a multiple contingency table with $\prod_{\mathbf{i=1}}^{\mathbf{j}} \mathbf{I_i}$ response patterns. If $\boldsymbol{\pi}$ denotes probability, $\boldsymbol{\pi}(\mathbf{X_t})$ represents the probability that a randomly selected case belongs to the latent t class, with t=1, 2,…, T.

The regular expression of LCMs is given by:

$$\pi_{Y_i} = \sum_{t=1}^{T} \pi_{X_t} \pi_{Y_i|X_t}, \quad (1)$$

with $\mathbf{Y_i}$ as the response-pattern vector of case i; $\boldsymbol{\pi}(\mathbf{X_t})$ the prior probability of membership in cluster t; and $\boldsymbol{\pi}_{\mathbf{Y_i|X_t}}$ the conditional probability that a randomly selected case has a response pattern $\mathbf{Y_i}$= (y1,…,yj), given its membership in the t class of latent variable X. The assumption of local independence needs to be verified, and therefore Eq. (1) is re-written:

$$\boldsymbol{\pi}_{\mathbf{Y_i}} = \sum_{\mathbf{t=1}}^{\mathbf{T}} \boldsymbol{\pi}_{\mathbf{X_t}} \prod_{\mathbf{i=1}}^{\mathbf{j}} \boldsymbol{\pi}_{\mathbf{Y_{ij}|X(t)}}, \text{ with } \sum_{\mathbf{i=1}}^{\mathbf{j}} \boldsymbol{\pi}_{\mathbf{Y_{ij}|X(t)}} = \mathbf{1}, \text{ and } \sum_{\mathbf{t=1}}^{\mathbf{T}} \boldsymbol{\pi}_{\mathbf{X_t}} = \mathbf{1} \quad (2)$$

A more detailed description of LCC analysis can be found in Sepúlveda (2004).

The estimation of the model is based on the nature of the manifest variables, since it is assumed that the conditional probabilities may follow different formal functions (Vermunt and Magidson, 2005). The method of *maximum* likelihood is used for estimating the model's parameters. Once the model has been estimated, the cases are classified into different classes by using the Bayes rule to calculate the *a posteriori* probability that each n subject comes from the t class (^ are the model's estimated values):

$$\boldsymbol{\pi}_{\mathbf{X_t|Y_i}} = \frac{\hat{\boldsymbol{\pi}}_{\mathbf{X_t}} \hat{\boldsymbol{\pi}}_{\mathbf{Y_i|X_t}}}{\hat{\boldsymbol{\pi}}_{\mathbf{Y_i}}} \quad (4)$$

In practice, the set of probabilities is calculated for each response pattern and the case is assigned to the latent case in which the probability is the highest. Thus, a specific passenger may belong to different latent cases with a specific percentage of membership (100% being the sum total of membership probabilities).

A priori, the number of cluster is unknown, meaning the aim is to find the model that can explain or adapt best to the data being used. LCC deals with model selection (number of clusters) by trying multiple models and computing various information criteria such as the Bayesian Information Criteria (BIC) (Raftery, 1986), Akaike Information Criterion (AIC) (Akaike, 1987), and Consistent Akaike Information Criterion (CAIC) (Fraley and Raftery, 1998). The appropriate number of clusters is the one that minimizes the score of these criteria, because the model is more parsimonious and adapts better to the study data (De Oña et al., 2013b).

2.2. Classification and Regression Trees (CART)

Service quality is then explored using Decision Trees (DTs) because its simplicity and graphic representation of their results and it enables to extract "If-Then" decision rules, providing explanations for the overall service quality evaluation. DTs were performed on the entire sample of users as well as particular groups of passengers identified.

A DT is an oriented graph formed by a finite number of nodes departing from the root node. DTs are built recursively, following a descending strategy, starting with the full data set (made by the root node). Using specific split criteria, the full set of data is then split into even smaller subsets. Each subset is split recursively until all of them are pure (when the cases in each subset are all of the same class) or their "purity" cannot be increased. That is how the tree's terminal nodes are formed, which are obtained according to the answer values of the target variable (De Oña et al., 2012).

CART is a particular methodology used for building binary Decision Trees in which the Gini Index can be applied as the splitting criterion. Depending on the nature of the dependent variable, CARTs develop classification trees (target variable is discrete) or regression trees (for a continuous target variable). Because this study aims to explore categorical variables (the target being passengers' "Overall Evaluation" with three levels: Poor, Fair and Good), classification trees were developed.

The development of a CART model generally consists of three steps: (1) growth of the tree, (2) the pruning process, and (3) selecting an optimal tree from the pruned trees. The tree growing entails recursive partitioning of the target variable to maximize ''purity'' in the two child nodes. By definition, the terminal nodes present a low degree of impurity compared to the root node. In the tree-growing stage, predictors generate candidate partitions (or splits) at each internal node of the tree; this calls for defining a suitable criterion for choosing the best partition (or the best split) of the objects. In turn, the Gini reduction criteria measures the ''worth'' of each split in terms of its contribution toward maximizing homogeneity through the resulting split. If a split results in the splitting of one parent node into B branches, the ''worth'' of that split may be measured as follows:

$$\text{Worth} = \text{Impurity (Parent node)} - \sum_{n=1}^{N} \text{P(n)} * \text{Impurity(n)}, \qquad (5)$$

where Impurity (Parent node) denotes the Gini measure for the impurity (i.e., non-homogeneity) of the parent node, and P(b) denotes the proportion of observations in the node assigned to branch b. The impurity measure, Impurity (node), may be defined as follows:

$$\text{Impurity (node)} = 1 - \sum_{i=1}^{I} \left(\frac{\text{number of class i cases}}{\text{all cases in the node}}\right)\hat{}2, \qquad (6)$$

When a node is ‘pure’ then Eq. (6) will have the minimum value, and its value will be higher for less homogeneous nodes. If one considers the definition of ‘‘worth’’ according to Eq. (5), a split resulting in more homogeneous branches (Child nodes) will have more ‘‘worth’’.

While developing a CART, this criterion is applied recursively to the descendents to achieve Child nodes having maximum worth which, in turn, become the parents for successive splits, and so on. The splitting process ceases only when there is no (or less than a pre-specified minimum) reduction in impurity and/or the minimum limit for number of observations in a leaf is reached. This process gives rise to a saturated tree that provides the best fit for the data set it was derived from, though it overfits the information contained within the data set and such overfitting does not help in accurately classifying another data set. Therefore, in developing a CART model the data is usually divided into two subsets, one for learning (or training) and the other for testing (or validation). The learning sample is used to split nodes, while the testing sample is used to compare the misclassification. The saturated tree is then constructed from the learning data.

Overly large trees could result in higher misclassification when applied to classify new data sets. To decrease its complexity, the tree is pruned in the second step according to a cost-complexity algorithm based on removing the branches that add little to the predictive value of the tree. The cost-complexity measure combines precision criteria as opposed to complexity in the number of nodes and processing speed, searching for the tree that obtains the lowest value for this parameter. Thus, with the last step, the optimal tree is obtained. A more detailed description of the CART method can be found in Breiman et al. (1984).

The importance of the variables that intervene in the model can also be derived from the CART method. The value of the standardized importance of independent variables reflects the impact of such predictor variables on the model (Kashani and Mohaymany, 2011).

Moreover, CART methodology provides effective ‘‘If-then’’ rules that make the model very practical and easy to interpret from the perspective of management by public transport operators and managers. Each decision tree gives as many rules as the existing number of terminal nodes by following the paths created between the root node and each terminal node. An “If-Then” rule is a conditional statement that provides a prediction of the target variable when a set of conditions is complied.

3. EXPERIMENTAL CONTEXT

The data used in this analysis comes from four Customer Satisfaction Surveys (CSS) conducted by the Transport Consortium of Granada in their metropolitan public bus transport service. This service is formed of 18 bus transport corridors, which serve most of the population living in the municipalities of the metropolitan area of Granada (Spain), with a total population of 505,875 in 2009. This year the metropolitan public bus system carried more than 10.5 million passengers. The number of trips per inhabitant and year was 21 and the number of passenger-km per year was 140.5 million.

Every year, the Transport Consortium of Granada takes on an expert company to develop surveys for passengers’ opinion of the service provided. To ensure coverage of the area and the customers, the surveys are conducted at the main bus stops of the different lines in the network, and respondents are randomly selected, establishing a minimum representativeness of certain segments of passengers (minimum stratification representativeness considering gender and age). Obtaining a representative public transport population sample is an important issue in order to avoid sample bias, hence the impossibility of generalizing results. However, in many cases public transport population characteristics are unknown because no national or regional travel habit survey has been performed before. Such is the case of the present experimental context.

This study involves 3,664 interviews collected in four consecutive CSSs developed from 2008 to 2011 (around 1,000 face-to-face surveys are conducted annually). The CSSs are divided into two main sections:

- The first section gives general information about the trip (time of the interview, bus stop, line, operator, origin, destination, etc.); socioeconomic characteristics of passengers (gender and age) and travel habits (travel reason, use frequency, type of ticket, private vehicle available, complementary modes from origin to bus stop, complementary modes from bus stop to destination, etc.).
- The second section of the survey is specifically about passengers' perception about service characteristics. First, the interviewers asked the passengers about their perception of performance with regards to 12 Service Quality (SQ) factors, on a cardinal scale from 0 to 10. Second, they asked the passengers to identify the three most important SQ factors for each of the 12 factors. And finally, they asked about the overall SQ perception based on a cardinal scale from 1 to 5. The variables used to measure the perception of the SQ attributes included: information, punctuality, safety on board, driver courtesy, bus interior cleanliness, bus space, bus temperature, accessibility to/from the bus, fare, speed, frequency of service and stops proximity to/from origin/destination.

The sample characteristics are represented in Table 1. There were more females than males. Half of the respondents had ages between 18 and 30, and a small proportion was over 60. The main reasons cited for travelling were occupation and studies, yet other reasons frequently given were going to doctor, shopping, or holidays. The results showed that most passengers travel almost every day (more than four times a week) or frequently (from 1 to 3 times a week). The consortium pass is the type of ticket most used, as opposed to the standard ticket, the senior citizen pass and others. The sample of users is equally distributed among those who had a private vehicle available for making the trip and those who did not. The majority of respondents accessed the bus service on foot (77% of the passengers), while some used other modes (urban bus, metropolitan bus, private vehicle, motorbike, bicycle, taxi or others). Likewise, almost all respondents accessed their destination from the bus stop on foot.

CHARACTERISTICS	**STATISTICS**
1.Gender	Male (32%), female (68%)
2.Age	18-30 (49%), 31-60 (40%), > 61 year-olds (11%)
3.Travel reason	Occupation (28%), studies (25%), doctor (11%), shopping (7%), holidays (6%), others (23%)
4.Use frequency	Almost diary (57%), frequently (22%), occasionally (13%), sporadically (8%)
5.Type of ticket	Consortium pass (67%), standard ticket (23%), senior citizen pass (7%), other ticket (3%)
6. Private vehicle available	Yes (47%), no (53%)
7. Complementary modes from origin to bus stop	On foot (77%), urban bus (18%), metropolitan bus (2%), private vehicle (1%), other mode (2%)
8. Complementary	On foot (95%), other mode (5%)

modes from bus stop to destination	

Table 1. Sample characteristics

VARIABLE	CATEGORIES
Gender	1.Male 2.Female
Age	1.{18-30} Young 2.{31-60} Middle 3.{>60} Old
Travel reason	1. Occupation 2. Studies 3. Others
Use frequency	1. Frequent 2. Sporadic
Type of ticket	1. Standard ticket 2. Consortium Pass 3. Senior Citizen Pass 4. Other
Private vehicle available	1. Yes 2. No
Complementary modes from origin to bus stop	1. On foot 2. Vehicle
Complementary modes from bus stop to destination	1. On foot 2. Vehicle

Table 2. Categorization of the variables

For the cluster analysis and the subsequent model calibration of the decision tree, some variables were categorized into a minor number of categories in order to achieve a sufficient representation of such classes. This is represented in Table 2. The variable "reason for travel" was reduced to the three most important categories (occupation, studies and other reasons). Frequency was reduced into two (frequent and sporadic). Passengers travelling almost daily and frequently were labeled as frequent passengers, and passengers travelling occasionally and sporadically were grouped and labeled as sporadic. The complementary modes of access from origin to bus stop, and from bus stop to destination, were narrowed down to just two categories (on foot or using a vehicle).

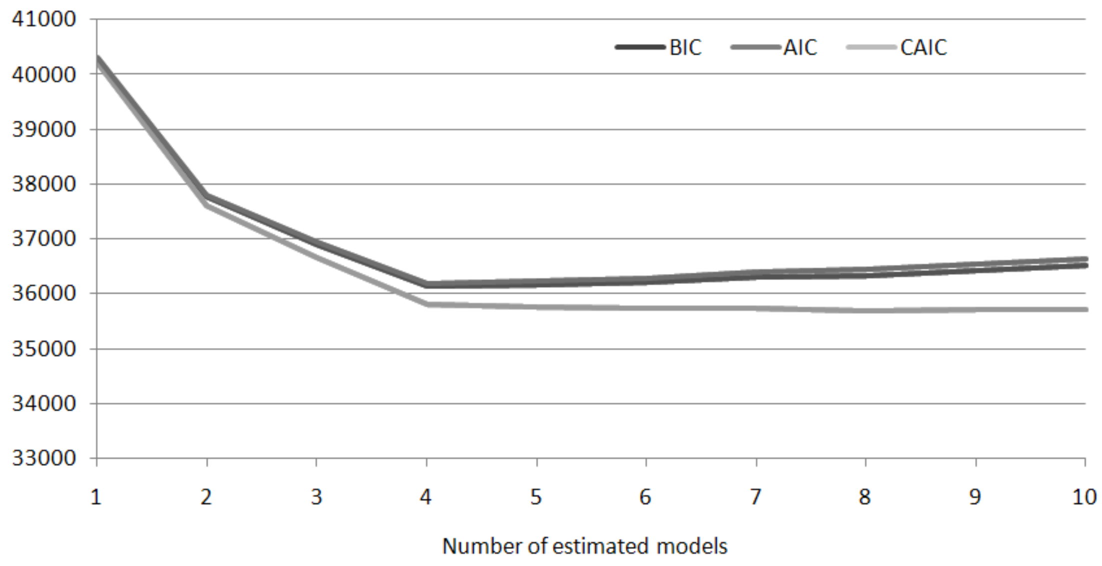

Figure 1. Model generated to select the best number of cluster.

4. RESULTS

4.1. Cluster analysis.

LCC analysis was performed using Latent GOLD software (v.4.0). Table 2 shows the 8 variables used in the analysis. To select the appropriate number of clusters in the final model, different numbers of clusters were tested, from one to ten. The parameters BIC, AIC and CAIC were used to choose the final number of cluster. Fig. 1 shows the evolution of BIC, AIC and CAIC for the 10 models. Increasing the number of clusters until four, the values of BIC, AIC and CAIC decline; however, when the number of clusters is bigger than 4, the values of the parameters increase. In addition, the entropy for model 4 is 0.766, which indicates a good separation between clusters (McLachlan and Peel, 2000). Therefore, the model selected is the one with 4 clusters.

The final model (4 clusters) was characterized by the proportion of each variable in each cluster. Following Depaire et al. (2008) and De Oña et al. (2013b), the clusters were analyzed and named based on their variable distributions. For example, if one cluster has 95% of travel reason being "studies", meaning this cluster would be the profile, which travels owing to studies reason.

Then it was necessary to identify the most important categories within each cluster for each variable (using the highest conditional probability obtained for a certain category of a variable given its membership to a specific cluster). This characterization was done using the variables that permitted differentiation between clusters.

The variables "Complementary modes from origin to bus stop" and "Complementary modes from bus stop to destination" did not prove useful in the characterization of the clusters because the highest value of probability was obtained for the same category of the specific variable in all of the clusters built, namely passengers "going on foot". In other words, this variable does not permit differentiation between the clusters.

VARIABLES	CATEGORY	Cluster1	Cluster2	Cluster3	Cluster4
Private Vehicle	No	61%	47%	43%	77%
	Yes	39%	53%	57%	23%
Travel Reason	Occupation	16%	62%	11%	1%
	Studies	68%	0%	2%	0%
	Others	16%	38%	87%	99%
Use Frequency	Frequent	99%	99%	32%	50%
	Sporadic	1%	1%	68%	50%
Ticket	Standard	11%	9%	65%	7%
	Senior Citizen Card	86%	90%	28%	13%
	Fass Card	0%	0%	0%	78%
Age	Young	95%	20%	37%	0%
	Middle	5%	78%	59%	1%
	Old	0%	2%	4%	99%
Gender	Men	36%	20%	36%	43%
	Women	64%	80%	64%	57%

Table 3. Variables, categories and probabilities of membership in the cluster.

Table 3 shows the six variables selected to characterize the clusters, along with their probability in each one of the 4 clusters identified.

- Cluster 1: This is the largest cluster (39% of the data). It includes men and women that are mainly young, with a probability of 95%. They are frequent users (with 99% of probability) without a private vehicle (in almost of 61% of the cases).Cluster 1 is characterized by passengers using the Consortium Pass in 86% of the cases analyzed. The travel reason is studies with 68% of probability. We will refer to these passengers as “Young students”.
- Cluster 2: This cluster represents 28% of the data. It is characterized by women (with a percent of almost 80%) of medium age (with 78% of probability), travelling because of occupation (62%), with frequent use in 99% of the cases and using the Consortium Pass (90%). We will refer to this cluster as “Working women”.
- Cluster 3: The size of this cluster is 23% of the data. Cluster 3 also is represented by women (64%), though sporadic, with 68% probability. A standard ticket is used in most of the cases (65%), and the travel reason is Other (87%). We named these passengers “Sporadic users”.
- Cluster 4: This is the smallest cluster, with 9% of the data, essentially formed by elderly (99%) women and men (43% men, 57% women), with no private vehicle (77% of probability). Most used the Senior Citizen Pass (78%), and the travel reason was other (in the 99% of the cases). This cluster is referred to as “Elderly passengers”

4.2. Decision trees

Five different classification trees were generated (Figures 2 to 6), one for the overall sample of users, and the other four corresponding to each of the detailed passengers’ profiles identified in the previous step. For each model, 20 variables were used as independent variables. To arrive at more applicable decision rules, and following previous studies (e.g., de Oña et al., 2014a) the response variable (overall SQ) and the independent variables related to SQ attributes (12) were re-coded in a reduced semantic scale. It was a three-point semantic scale, comprising the rates from 0 to 4 as POOR, from 5 to 7 as FAIR, and from 8 to 10 as GOOD. If another recodification of the variables was applied, it is possible that the trees would have been modified. We believe that this recodification is reasonable, because an evaluation rate under 5 about any characteristic implies that aspect of the service does not work well.

For the overall sample of passengers (Figure 2) the tree achieved an accuracy rate of 68.18%, while the accuracy rate obtained in the trees built for the four clusters (Figure 3, 4, 5 and 6) ranged between 64.84% in Cluster 3 to 76.26% in Cluster 4. The tree built for the overall sample was the most complex, with the largest structure. It produced 16 nodes, of which 9 were terminal nodes. The predictors of this classification tree were the variables Frequency, Punctuality, Information, Safety, Speed, Accessibility and Temperature. Some of these variables were also identified as predictors in the other trees built with the cluster samples. The primary split for the overall sample was Frequency, as happened in Cluster 2 “Working women” (Figure 4) and Cluster 3 “Sporadic users” (Figure 5). It keeps towards the left branch of the trees those passengers that perceive the Frequency as POOR, away from those that perceive it as FAIR or GOOD (right branch of the trees). The proportion of passengers evaluating the overall quality of the service as POOR increased significantly from the root node to Node 1 in the three models. Node 1 is constituted by the passengers that have a POOR evaluation of Frequency, and represents more than 20% of the sample of each tree.

The classification tree generated for Cluster 1 “Young student” (Figure 3), presents a different structure. The first variable used as predictor was Punctuality. A POOR perception of Punctuality and a POOR perception of Safety led this group of passengers towards a POOR overall SQ evaluation (Node 3). On the other hand, if Punctuality is perceived as FAIR or GOOD (right branch of the tree), all the terminal nodes predict a FAIR or GOOD overall SQ evaluation, even though other variables are involved in the overall evaluation, and will influence the probability of reaching a GOOD service assessment.

In Cluster 3, “Sporadic users” (Figure 5), and Cluster 4, “Elderly passengers” (Figure 6), further variables not identified before were selected as significant by the algorithm. These variables are Proximity for Cluster 3, and Proximity and Cleanliness for Cluster 4. In addition, for this last group, Information acts as the primary splitter of the tree. With POOR perception of Information, the probability of having a POOR overall SQ evaluation increases considerably, changing from 7.4% at the root node to 35.1% at Node 1. In addition, if Proximity is also perceived as POOR, the probability of having a POOR overall SQ evaluation increases to 75.0%.

Following the paths created between the root node and each terminal node at the models built, informative “If-Then” rules are extracted, and interesting relationships of variables can be discovered, in order to better understand passengers’ reflections about the quality of the service. For example, for cluster 4, the transport company faces the following rules:

- Node 3: IF (Information is POOR AND Proximity is POOR) THEN (overall SQ=POOR)
- Node 5: IF (Information is POOR AND Proximity is FAIR or GOOD AND Cleanliness is POOR or FAIR) THEN (overall SQ=FAIR)
- Node 6: IF (Information is POOR AND Proximity is FAIR or GOOD AND Cleanliness is GOOD) THEN (overall SQ= GOOD)
- Node 2: IF (Information is FAIR or GOOD) THEN (overall SQ=GOOD)

In this case, the company can decide the strategy based on its resources limitations. Perhaps increasing the quality of Proximity removes POOR evaluations about the service, although it is not affordable for the company, while increasing the quality of Information is easier, achieving directly GOOD evaluations about the service. These rules allow for consideration of more than one attribute at the same time.

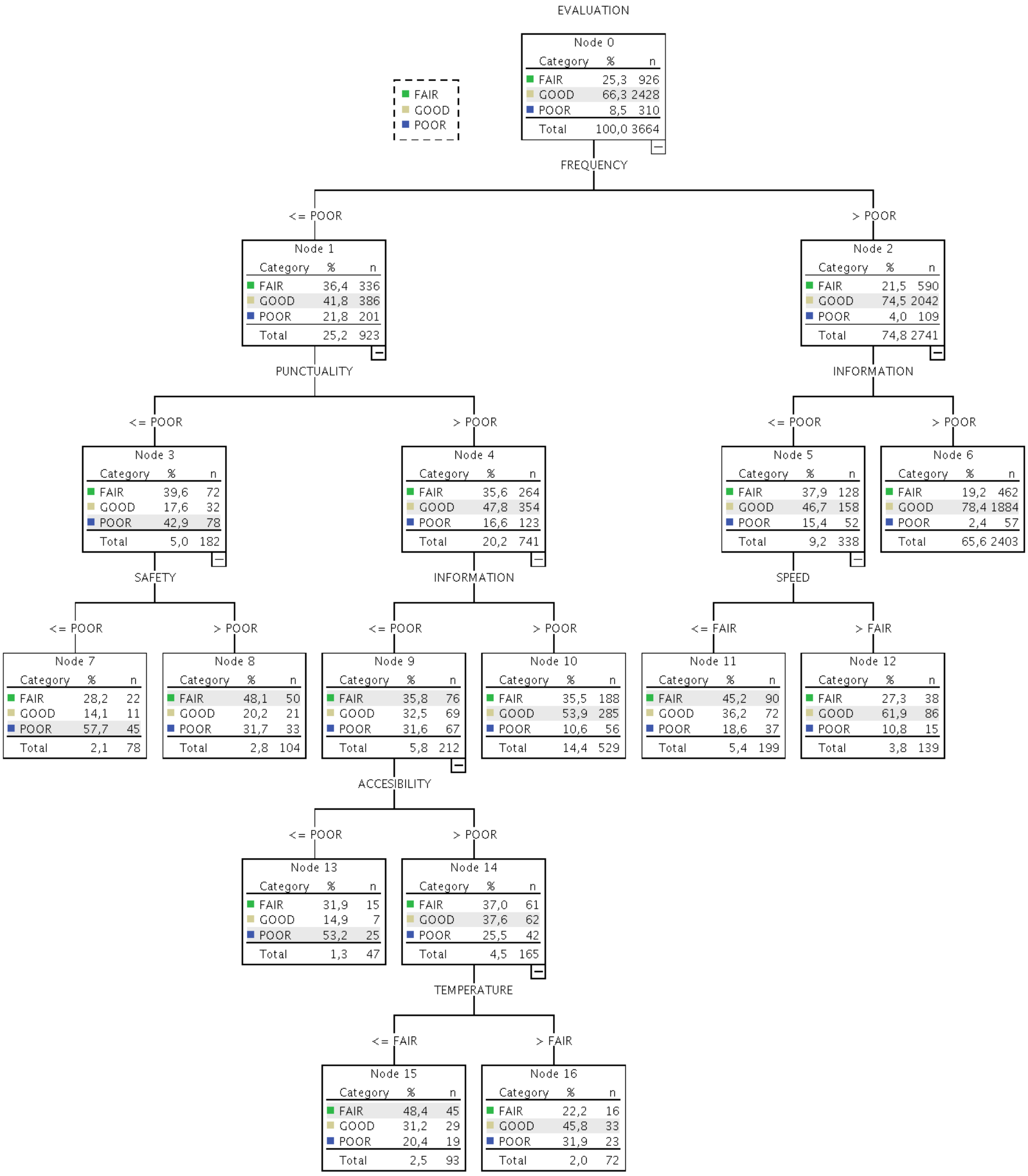

Figure 2. CART built for the overall sample of passengers

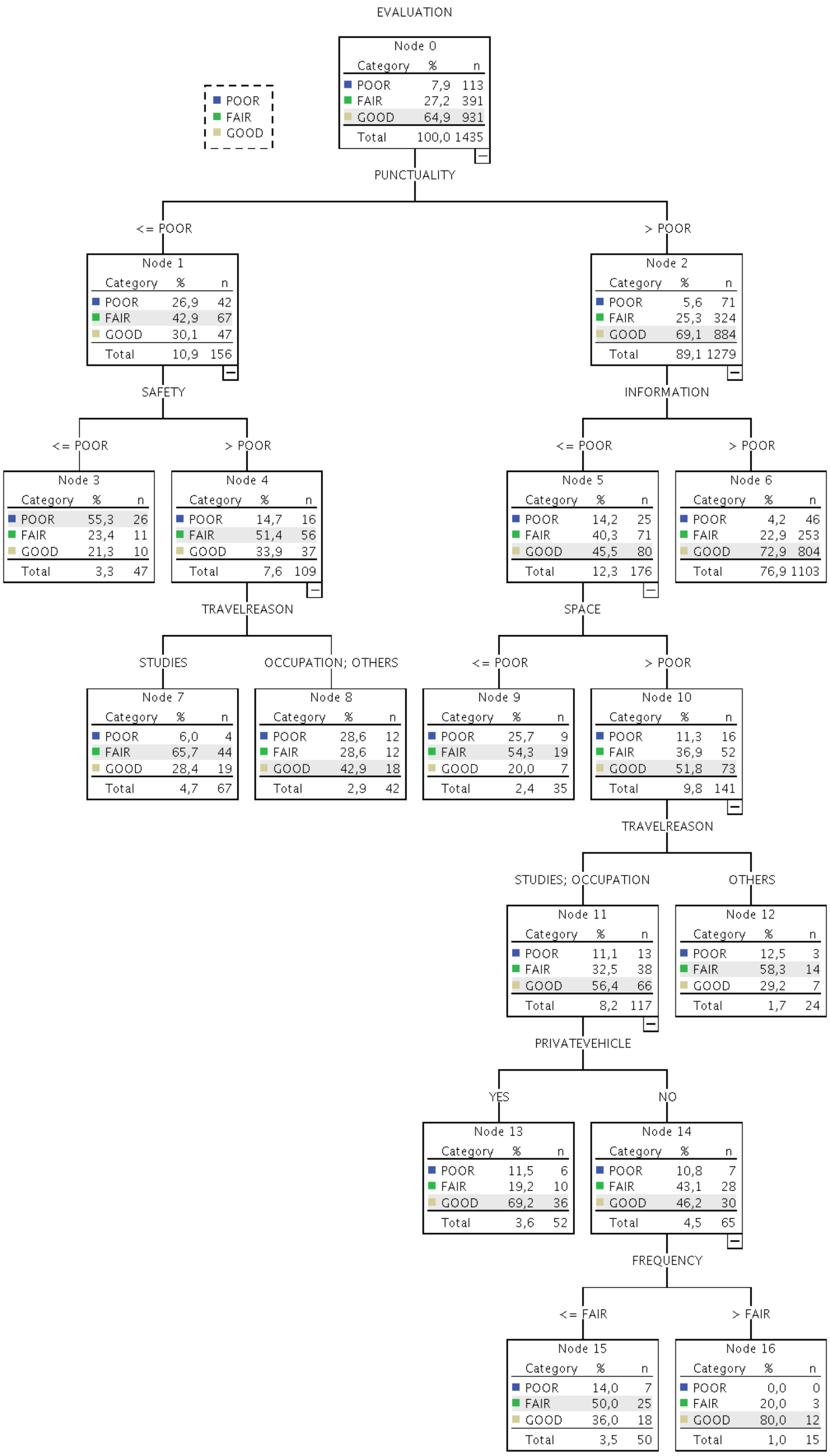

Figure 3. CART built for the Cluster 1

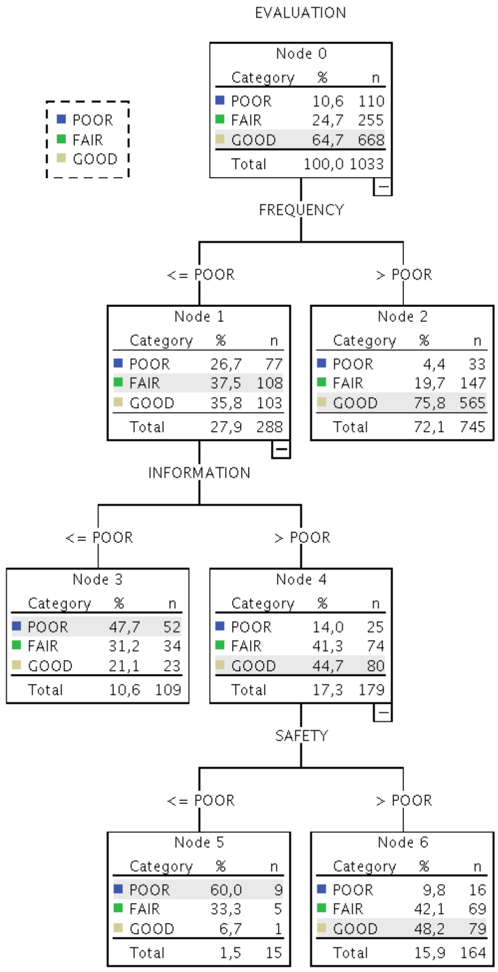

Figure 4. CART built for the Cluster 2

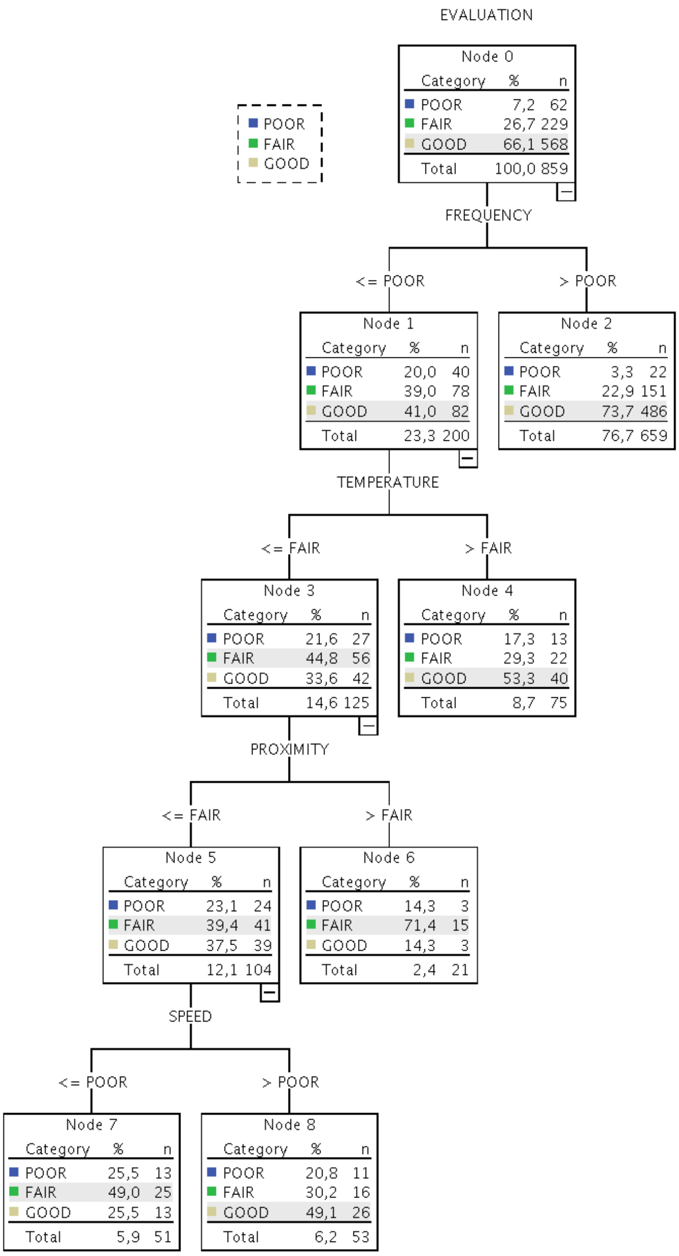

Figure 5. CART built for Cluster 3

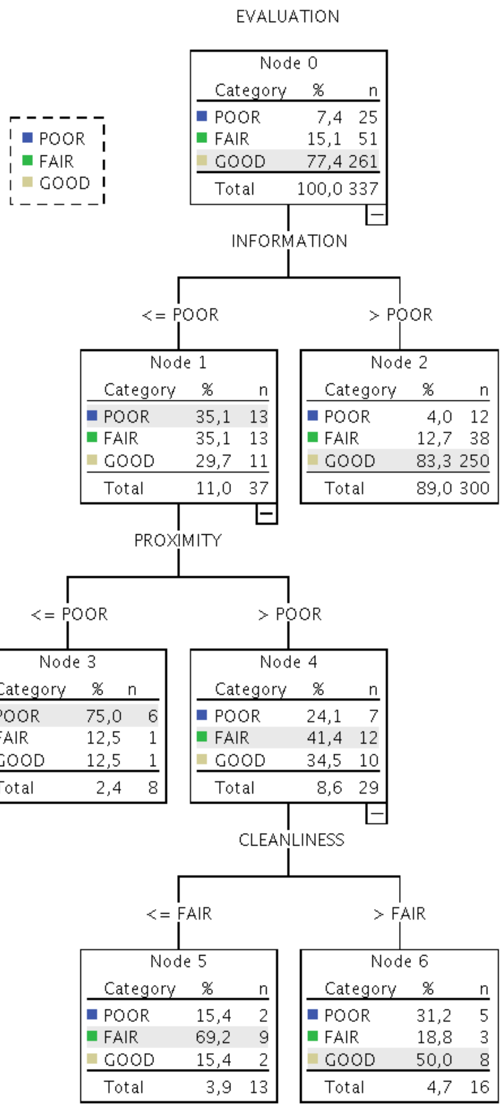

Figure 6. CART built for the Cluster 4

In addition to the graphic representation of the trees, the importance index (Kashani and Mohaymany, 2011) reflects the relative importance of the variables for each model. This is one of the most valuable outcomes provided by CART analysis. This information is obtained for all the independent variables, identifying which ones are the most relevant.

Table 4 shows the importance ranking for the independent variables of the overall SQ for the whole sample of passengers and for each one of the clusters. For the overall SQ, Frequency and Punctuality are identified as most important. Many other authors (e.g., de Oña et al., 2012; 2013a; 2014a; dell'Olio et al., 2010; 2011; Eboli and Mazzulla, 2008; 2010) have also identified these variables as key factors for public transport services. Other highly relevant variables are Speed (de Oña et al., 2013a), Safety (Mahmoud and Hine, 2013) and Space (Mahmoud and Hine, 2013).

In contrast, Accessibility was identified as a variable having limited relevance for users, both in the overall sample and for each identified cluster. Similarly, the multicriteria evaluation of current and potential user perception towards bus transit services in Belfast city by Mahmoud and Hine (2013) found that potential users assigned a higher importance to indicators related to the Access to Service and Operation attributes, while current users assigned a higher importance to indicators related to Safety and Security and Service Design. Bus stop location was a particularly important variable for both groups of passengers (represented by the variable Proximity in this research); for potential users the variables Ease of purchasing tickets and Ease of access to bus stops and stations were identified as key (represented as the variable Accessibility in this research). Such findings may indicate that service Accessibility is a key factor to attracting new users towards the service (potential users). Thus, public transport planners would do wisely to focus on this service aspect in order to achieve a behavioral shift from the private car to public transport modes.

Punctuality is the most important characteristic of the service for passengers of Cluster 1, mainly made up of young travelers who study, and must arrive on time for lessons or exams. Next, safety, courtesy and information are highly valued by the young student. Because they tend to use public transport every day, it is important for them to travel safely and with pleasant people. In Cluster 2, Working women, the most important variables were found to be Information, Frequency and Punctuality. For this group the main travel reason is occupation, meaning good Frequency may be more essential than Punctuality —timetables for workers are usually more flexible than for students. Space, Speed and Safety are further variables of high influence in Cluster 2. Speed is an important service factor when passengers can rely on their own private vehicle (as happens in Cluster 2 and Cluster 3, where half of the passengers have a private vehicle available). In that case, speed becomes a competitive characteristic for their modal choice. Likewise, as they are non-captive users of bus transit, comfort (e.g. Space) can weigh heavily on their modal decision.

Information is the most important characteristic of service for Cluster 4 (the elderly), and Cluster 2 ("working women"). It also has a high influence for Cluster 1 "young students", representing Cluster 1 and 2 passengers that travel frequently. Older people have more difficulty understanding how the service works, and interpreting timetables, maps, panels, etc. For this reason they need simple yet adequate information about the service, which often has to be complemented with driver responses. This is why the courtesy of the employee is the second most important characteristic of service in Cluster 4.

OVERALL SAMPLE		CLUSTER 1		CLUSTER 2		CLUSTER 3		CLUSTER 4	
VARIABLE	**IMP.**	VARIABLE	**IMP.**	**VARIABLE**	**IMP.**	**VARIABLE**	**IMP.**	**VARIABLE**	**IMP.**
FREQUENCY	100.0	PUNCTUALITY	100.0	INFORMATION	100.0	FREQUENCY	100.0	INFORMATION	100.0
PUNCTUALITY	93.2	SAFETY	87.6	FREQUENCY	96.8	SPEED	80.6	COURTESY	44.6
SPEED	70.4	COURTESY	59.9	PUNCTUALITY	83.0	PROXIMITY	54.2	SPEED	27.9
SAFETY	68.1	INFORMATION	55.2	SPACE	82.1	TEMPERATUR	21.8	CLEANLINESS	24.3
SPACE	67.3	TRAVELREAS	28.7	SPEED	73.0	TRAVELREAS	18.1	SPACE	17.8
TEMPERATURE	63.1	CLEANLINESS	17.9	SAFETY	71.9	CLEANLINESS	8.3	PROXIMITY	17.3
CLEANLINESS	59.3	SPACE	13.4	TEMPERATUR	64.0	INFORMATION	7.5	TEMPERATUR	15.0
INFORMATION	49.6	FREQUENCY	11.0	CLEANLINESS	62.0	SPACE	6.9	SAFETY	9.8
PROXIMITY	43.1	PRIVATEVEHI	10.0	FARE	58.1	FARE	6.5	FREQUENCY	9.2
COURTESY	41.6	ACCESIBILITY	9.7	ACCESIBILITY	56.3	SAFETY	6.1	TICKET	6.3
ACCESIBILITY	9.4	TEMPERATUR	6.0	PROXIMITY	36.5	TICKET	4.9	ACCESIBILITY	4.9
FARE	3.7	MODESFROM	3.1	COURTESY	35.8	PRIVATEVEH	2.9	PUNCTUALITY	4.8
AGE	2.4	USEFREQUENC	1.8	AGE	0.7	USEFREQUEN	2.8	AGE	1.1
TRAVELREASON	1.1	TICKET	1.0			ACCESIBILITY	2.6	GENDER	0.8
USEFREQUENCY	.8					AGE	2.2		
TICKET	.5					PUNCTUALITY	1.3		
MODESTO	.2					COURTESY	0.6		
MODESFROM	.1					MODESTO	0.4		

Table 4. Importance of the variables for the Overall Sample and clusters of passengers.

Frequent passengers (Clusters 1 and 2) place great importance on the quality of Information, as they tend to suffer more from changes in routes and timetables, often implying delays. Likewise, Safety is a key factor for them. While for "Young students" of Cluster 1 Information and Safety are mostly the important service characteristics, for "Working women" of Cluster 2 a large group of variables exerts a noteworthy influence on their overall service quality evaluation, perhaps because they are non-captive users of the bus service and many characteristics are considered before taking their modal choice.

On the contrary, sporadic passengers who are not elderly, grouped mostly in Cluster 3, are not very concerned about Information. Instead, they stress the relevance of Frequency. As they do not know the timetables, they would want service as frequently as possible. Interestingly, for sporadic users Punctuality is not important (Cluster 3), which is also true of the elderly, who may have plenty of time (Cluster 4). Punctuality is a key factor for frequent users (Clusters 1 and 2), however.

These differences among clusters support the benefit of stratifying the sample of passengers in order to become more familiar with passenger preferences and needs regarding service. Such knowledge helps transport planners to develop personalized marketing rather than generalized interventions. In fact, the real factors that are important for passengers may be masked when all of them are analyzed as a whole.

According to these results, some degree of personalized marketing could be done taking into account the key factors identified for each cluster. For example, in Cluster 3 "sporadic users", a marketing campaign might be designed to attract new potential users with characteristics similar to those identified for this group of current users. The marketing campaign would, ideally, consist of information about the service frequency, comparative information about travel times using the car versus the bus service, assessment of the time wasted in traffic jams of needed to find a parking place, maps with the bus stop location, parking areas near the bus network, shopping, hospital and business areas, and so on, given that this group of potential users would most likely use the bus service for reasons related to doctor visits or shopping.

For example, in Cagliari (Italy) an experimental program implemented to promote the use of a light rail service (Sanjust et al., 2014) consisted of personalized travel planning actions and public transport information and marketing campaigns. After this promotional program, it was found that the number of light rail passengers had increased by 30%. Moreover, the authors estimated that the total investment in the promotional program could be recovered over the following two years.

5. CONCLUSIONS

An analysis of service quality in a public bus service of Granada was conducted by using cluster analysis and decision trees techniques. Data from various customer satisfaction surveys carried out over the period 2008-2011 were used. The key factors influencing service quality evaluation were identified, and significant differences were determined across different groups of passengers. Based on the findings, public transport authorities and operators are able to develop specific personalized marketing strategies. As such personalization improves passengers' satisfaction and loyalty, this information serves to improve sales and profits in the company.

Normally, the frequency of use, gender, age and/or minimum income are criteria used for the stratification of passengers. This study entails a more advanced segmentation, not applied before in public transport service quality, by considering at the same time various socioeconomic characteristics of the users and their travel habits. Detailed profiles of users that have more homogeneous opinions about the service were discerned. This help public transport mangers to better understand passengers' behavior and to formulate personalized marketing focused on these groups.

Service quality was subsequently analyzed across the overall sample of users and across the groups of passengers identified beforehand, using decision trees, which made it possible to determine the impact of the variables upon the dependent variable (overall SQ), while also identifying patterns and relationships among the independent variables that help explain the dependent one.

The key factors influencing transit passengers are different according to passengers' profiles; due to they have different needs and preferences. Whereas for the overall sample of users the most important variables for the service quality evaluation are Frequency, Punctuality, Speed, Safety and Space, these variables change when specific groups of passengers are analyzed. Cluster analysis identifies four groups of passengers, representing diverse profiles. Cluster 1 comprises young passengers with frequent trips for academic reasons, using a consortium pass, and not having a private vehicle. For this sort of passenger, the most important variable was Punctuality, maybe because of lessons or exams. Middle age women, travelling frequently for occupation reasons and using the consortium pass, represent Cluster 2. The most important variables for this cluster were Information and Frequency. The timetable of working people is somewhat more flexible than for students, so a higher frequency is preferred to Punctuality. For the other clusters (3 and 4) the most determinant variables in overall evaluation differed substantially.

Some interesting findings of this analysis can be summed up as follows:

- Differences among Frequent passengers (Clusters 1 and 2) and "Sporadic passengers" (Cluster 3). Frequent passengers value specific variables such as Information and Safety, whereas for Sporadic passengers they are not so important;

- For passengers having a private vehicle available for making the trip (Clusters 2 and 3), Speed becomes a decisive competitive factor behind their modal choice;
- Information has substantial impact on frequent passengers' evaluations (Clusters 1 and 2), yet in the case of "Elderly passengers" (Cluster 4), it is the most important variable. This information is not discovered when the overall sample is analyzed.

These research findings demonstrate that passengers' opinions are very heterogeneous, and that the personalized analysis is a successful approach for identifying needs and requirements in order to detect specific patterns among the service characteristics (following the path of the decision trees) as well as the extent of influence that certain variables have on different user profiles. Some information and details about service quality evaluation could be masked if data are treated globally. Indeed, Ory and Mokhtarian (2005) undertook a project whose main conclusions were that travellers' attitudes and personality were more important determinants of travel pleasure than the more objective travel amounts.

Such issues hold significance for transport planners, who, in order to formulate successful incentives for promoting public transport services, should target the users they wish to engage. Attending to preferences and needs through personalized marketing is more effective than a generic framework of action. Moreover, essential and effective measures for promoting the use of public transport could be launched at little expense to public authorities (Sanjust et al., 2014), and the total investment may be compensated in a short period of time. Although public transport operators have not widely implemented this sort of program to date, their sales and profitability would rise if they did. Public transport authorities should increase their willingness to move in this direction. Furthermore, transport researchers have been recently motivated by the introduction of happiness attributes in their transportation models to better understand the decision process of transport users (Duarte et al., 2008).

Still, the specific findings of this paper cannot be extrapolated to other regions or other PT services (such us urban PT, or even metropolitan or suburban PT services involving modes of transport other than the one analyzed here) because the performance characteristics and passenger profiles and requirements differ widely among transit services. Even so, these results should not be extrapolated to other regions, or types of PT services, the fact is that the Latent Class Cluster methodology represents a powerful and suitable tool for extracting specific profiles of passengers. This permits public transport managers to better understand passengers' behavior paying attention to their profiles and the implementation of specific campaigns and better oriented system management, in terms of the perceived service quality of different user groups. This paper reports how it is possible to identify specific passengers' profiles in a transit service in order to perform more efficient personalized marketing.

Finally, DT methodology has some advantages inherent to non-parametric models, as it does not require prior probabilistic knowledge on the study phenomena, and there are no model assumptions or pre-defined underlying relationships between variables; and some advantages are particular to DT models, such us the simplicity of interpreting the results for transport operators. The graphic representation and the practicality of extracting "If-Then" rules can facilitate policy making, allowing a given company to choose a strategy in view of their resources and limitations. At the same time this methodology has some disadvantages, as it does not provide a confidence interval or probability level for the splitters and predictions in the model (Chang and Wang, 2006) as traditional parametric models do; and once the model makes a decision about a variable on which to split the node, the decision cannot be revised or improved, due to the absence of a backtracking technique (Xie et al., 2003).

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