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

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# 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 concerning the service. This approach made it possible to detect specific requirements and needs regarding the quality of service and to 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 evaluations. Cluster analysis identified four groups of passengers. Comparisons using decision trees among the overall sample of all users and the different groups of passengers identified by cluster analysis led to the discovery of differences in the key attributes encompassed by 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 that were identified to address 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 to make its use more appealing (Paquette et al., 2012). Moreover, improvements in public transport services may influence user satisfaction with travel conditions and, as a consequence, individuals' evaluations of quality of life on the whole (Ettema et al., 2011). Such "transport happiness" as part of an 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 analysing service quality (service managers' perspective vs. passengers' perspective), significant discrepancies may exist regarding the level of quality provided and what factors are crucially 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) claimed 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 analyse service quality based on passenger opinion. Indeed, users are the ones who suffer from 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 to design adequate interventions and strategies.

The primary problem to be faced along the way is the subjective nature of such measurements, which consist of fuzzy and heterogeneous passenger assessments. Moreover, passengers have different perceptions about each service attribute due to their specific needs and preferences toward the service. The resulting dispersion of responses reduces the reliability of service quality evaluation in terms of the influence each attribute exerts on overall service quality (i.e., attribute 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), as variation in user perception is incorporated in the parameters of the model. Alternatively, stratifying the sample of users on segments of passengers with more uniform opinions regarding the service represents another option for resolving the heterogeneity limitation.

Several studies stratify survey samples to reduce 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, segmentation is based on methodological decisions or the desire to study a specific problem. Expert knowledge can lead to workable segmentation of the data; however, it does not guarantee that each segment consists of a homogeneous group. Therefore, transit service quality analysis can 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 analysis, for example. 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. Thus, in this paper, CA is applied to address passenger heterogeneity, given that the technique stratifies the sample of passengers into groups with common characteristics and thus into groups with more homogeneous perceptions regarding the service. Moreover, CA not only helps to address heterogeneity as other techniques used before, such as discrete choice models with random parameters or traditional stratification, but it also identifies specific passenger profiles using the transit service, allowing better understanding of passenger behaviour.

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 expressly to 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 behaviour (e.g., reduce car use and increase cycling, walking, car sharing and the use of public transport). Many studies demonstrate that customized information is more effective than mass communication when involving individuals and changing travel behaviour (Gärling and Fujii, 2009).

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

Traditionally, service quality assessment has involved regression models, such as logit or probit (Eboli and Mazzulla, 2008, 2010; Hensher, 2003; dell'Olio et al., 2011) or structural equation models (De Oña et al., 2013a, Eboli and Mazzulla, 2007, Eboli and Mazzulla, 2012; Irfan et al., 2011). However, most of these models have certain limitations because predefined 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. These resolve some limitations found in traditional models, given that they are non-parametric techniques that do not require prior probabilistic knowledge of the phenomena of interest. Garrido et al. (2014) used an artificial neural network approach for analysing service quality in a metropolitan bus service, by comparing three different algorithms to find the most reliable. 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 also 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 of its simplicity and graphic representation of results (De Oña et al., 2015). For this reason, in this research, service quality evaluation is 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 to obtain segments of the whole sample of users; these segments represent passenger profiles. Next, service quality is explored using CART methodology performed on the entire sample of users, as well as on particular groups of passengers identified.

### 2.1. Cluster Analysis

The main aim of Cluster Analysis (CA) is to classify the data into groups (clusters) with similar characteristics, attempting to maximize the similarity between in-cluster elements and the dissimilarity between inter-cluster elements (Fraley and Raftery, 1998). 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 the single linkage method (Hair et al., 1998; Magidson and Vermunt, 2002; Vermunt and Magidson, 2005). Two of these advantages are the ability to use different types of variables (frequencies, categorical, metric variables) with no need for prior standardization that could alter the results; and the availability of several statistical criteria that help to decide the most appropriate number of clusters.

The formulation of the LCC is as follows: we are 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; 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:

$$\pi_{Y_i} = \sum_{t=1}^{T} \pi_{X_t} \pi_{Y_i|X_t}, \tag{1}$$

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; therefore, Eq. (1) is re-written as follows:

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

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 because 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 parameters. Once the model has been estimated, the cases are classified into different classes using Bayes' rule to calculate the *a posteriori* probability that each n subject comes from the t class (^ are the model's estimated values):

$$\boldsymbol{\pi}_{\mathbf{X_t|Y_i}} = \frac{\widehat{\boldsymbol{\pi}}_{\mathbf{X_t}} \widehat{\boldsymbol{\pi}}_{\mathbf{Y_i|X_t}}}{\widehat{\boldsymbol{\pi}}_{\mathbf{Y_i}}} \tag{4}$$

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 clusters is unknown, meaning the aim is to find the model that can explain or adapt best to the data being used. LCC addresses model selection (including determining the 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 such a model is more parsimonious and adapts better to the study data (De Oña et al., 2013b).

### 2.2. Classification and Regression Trees (CART)

A decision tree (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 splitting criteria, the full set of data is subsequently split into even smaller subsets. Each subset is split recursively until all of them are pure (i.e., when the cases in each subset are all of the same class) or until their "purity" cannot be increased. Thus, the tree's terminal nodes are obtained according to the final 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 (when the target variable is discrete) or regression trees (when the target variable is continuous). 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) growing the tree, (2) pruning the tree, and (3) selecting an optimal tree from the pruned trees. 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; such splitting calls for suitable criterion for choosing the best partition (or the best split) of the objects. 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:

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

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:

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

When a node is "pure", then Eq. (6) will have the minimum value, and its value will be higher for less homogeneous nodes. By examining the definition of "worth" according to Eq. (5), it is observed that a split resulting in more homogeneous branches (Child nodes) will have more "worth".

When developing a CART, this criterion is applied recursively to the descendants 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 are 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) by 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 highly practical and easy to interpret from the perspective of management by public transport operators and managers. (An "if-then" rule is a conditional statement that provides a prediction of the target variable when a set of conditions is obeyed). 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.

## 3. EXPERIMENTAL CONTEXT

The data used in this analysis come 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. That year the metropolitan public bus system carried more than 10.5 million passengers; the average number of trips per inhabitant was 21, and the total transport volume was 140.5 million passenger-km.

Every year, the Transport Consortium of Granada commissions a specialized contractor to develop surveys of passenger 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 representation of certain segments of passengers (minimum stratification representation considering gender and age). Obtaining a representative public transport population sample is an important requirement to avoid sample bias; otherwise, results cannot be generalized. 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 in 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 obtains general information about the trip (e.g., time of the interview, bus stop, line, operator, origin, and destination); socioeconomic characteristics of passengers (gender and age) and travel habits (e.g., travel reason, use frequency, type of ticket, private vehicle available, complementary modes from origin to bus stop, and complementary modes from bus stop to destination).

- The second section of the survey specifically addresses passenger perception about service characteristics. First, the interviewers asked the passengers about their perception of performance with regards to twelve 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 twelve factors. Finally, they asked about 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 stop proximity to/from origin/destination.

The sample characteristics are represented in Table 1. There were more females than males. Half of the respondents were between 18 and 30 years of age, and a small proportion were over 60. The main reasons cited for travelling were occupation and studies, while other reasons frequently given were doctor visits, shopping, or holidays. The results showed that most passengers travelled almost every day (more than four times a week) or frequently (from 1 to 3 times a week). The consortium pass was the type of ticket most used, as opposed to the standard ticket, the senior citizen pass and others. The sample of users was 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). 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 modes from bus stop to destination | On foot (95%), other mode (5%) |

**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 grouped into a smaller number of categories to achieve a sufficient representation of such classes. This grouping 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 labelled as frequent passengers, and passengers travelling occasionally and sporadically were grouped and labelled as sporadic. The complementary modes of access from origin to bus stop, and from bus stop to destination, were narrowed to only two categories (on foot or using a vehicle).

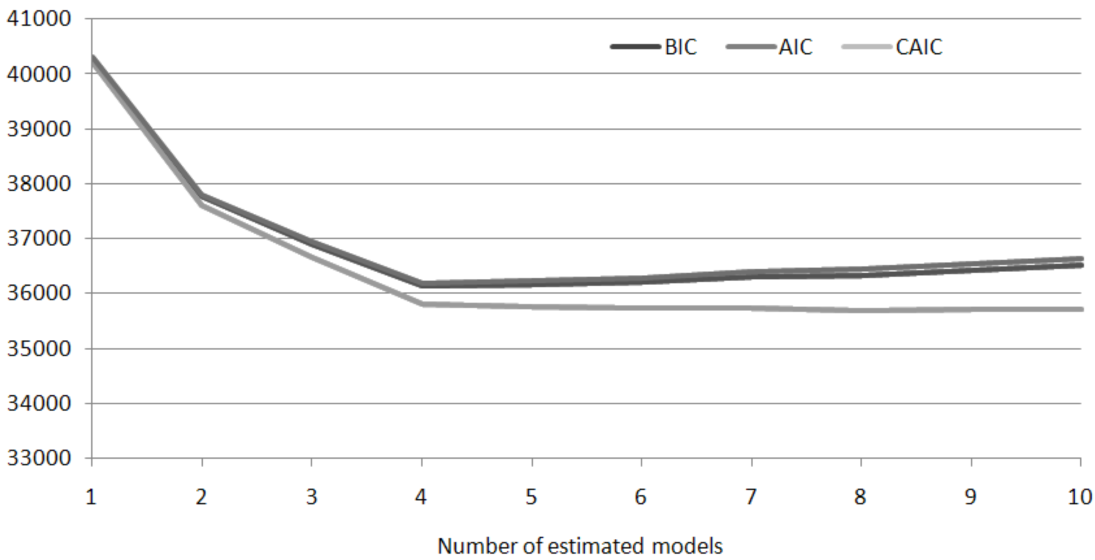


**Figure 1. Model generated to select the best number of cluster.**

## 4. RESULTS

### 4.1. Cluster analysis.

LCC analysis was performed using Latent GOLD software (v.4.0). Table 2 shows the eight 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 clusters. Fig. 1 shows the evolution of BIC, AIC and CAIC for the ten models. As the number of clusters is increased from one to four, the values of BIC, AIC and CAIC decline; however, when the number of clusters is larger than four, the values of the parameters increase. In addition, the entropy for the four-cluster model is 0.766, which indicates a good separation between clusters (McLachlan and Peel, 2000). Therefore, the four-cluster model was selected.

This model 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 were to feature a 95% value of the travel reason being "studies", this cluster would represent the passenger profile associated with travelling due to studies.

Thus, 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 in a specific cluster). This characterization was performed 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). The cluster includes men and women who are mainly young, with a probability of 95%. They are frequent users (with 99% probability) without a private vehicle (in almost 61% of the cases). Cluster 1 is characterized by passengers using a consortium pass in 86% of the cases analyzed. The travel reason is studies, with 68% probability. We refer to these passengers as "Young students".

- Cluster 2: This cluster represents 28% of the data. The cluster is characterized by women (with a percentage of almost 80%) of medium age (with 78% probability), travelling because of occupation (62%), with frequent use in 99% of the cases and using a consortium pass (90%). We refer to this cluster as "Working women".
- Cluster 3: This cluster represents 23% of the data. Cluster 3 is also 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% probability). Most used a senior citizen pass (78%), and the travel reason was "other" in 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 passenger 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. This three-point semantic scale labelled 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 and 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 toward 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 to be used as predictor was Punctuality. A POOR perception of Punctuality and a POOR perception of Safety led this group of passengers toward 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 were extracted, and interesting relationships of variables could be identified to elucidate passenger reflections regarding 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 on a strategy based on its resource 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, thereby achieving GOOD evaluations about the service. These rules allow for consideration of more than one attribute at the same time.

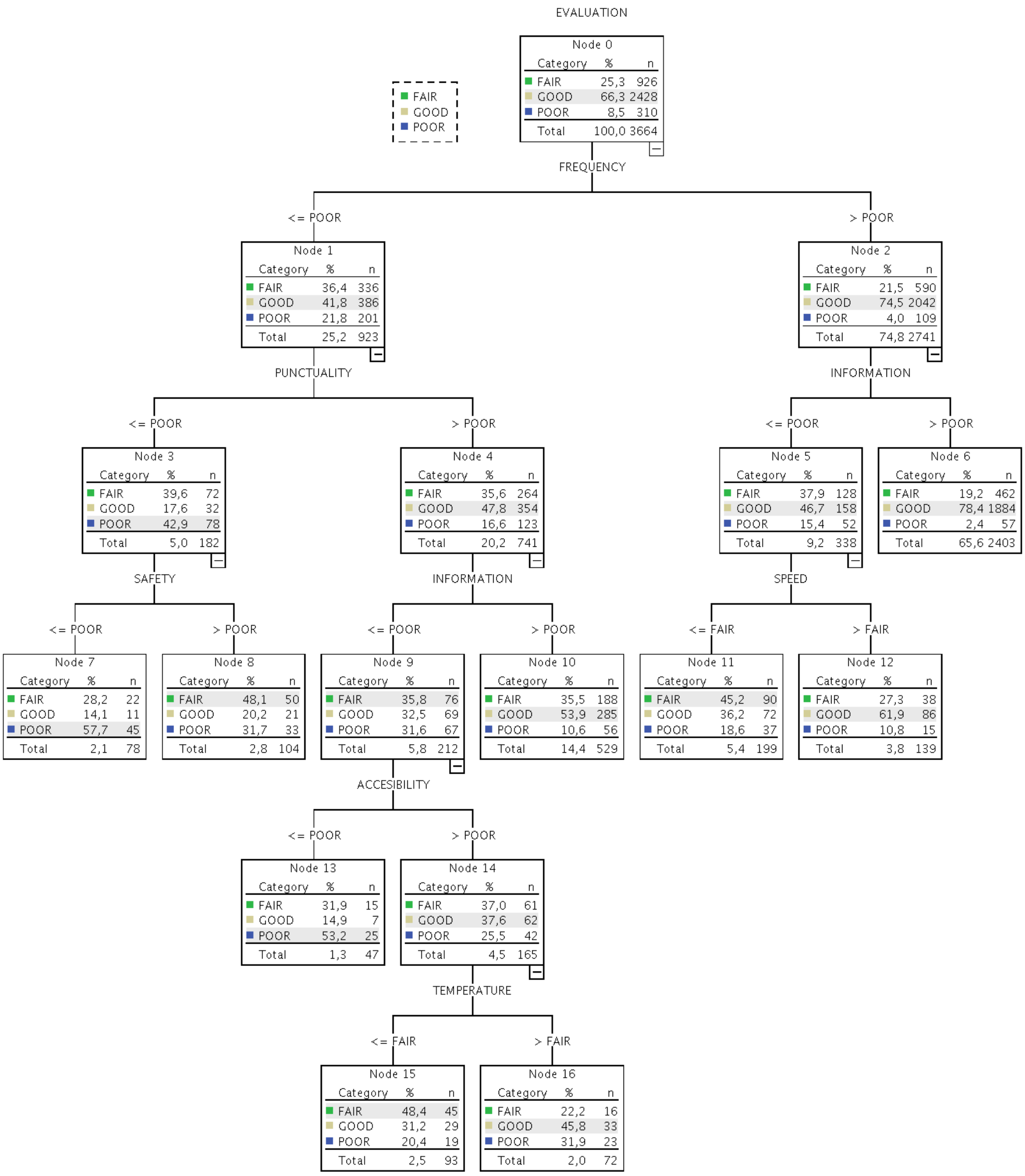


**Figure 2. CART built for the overall sample of passengers**

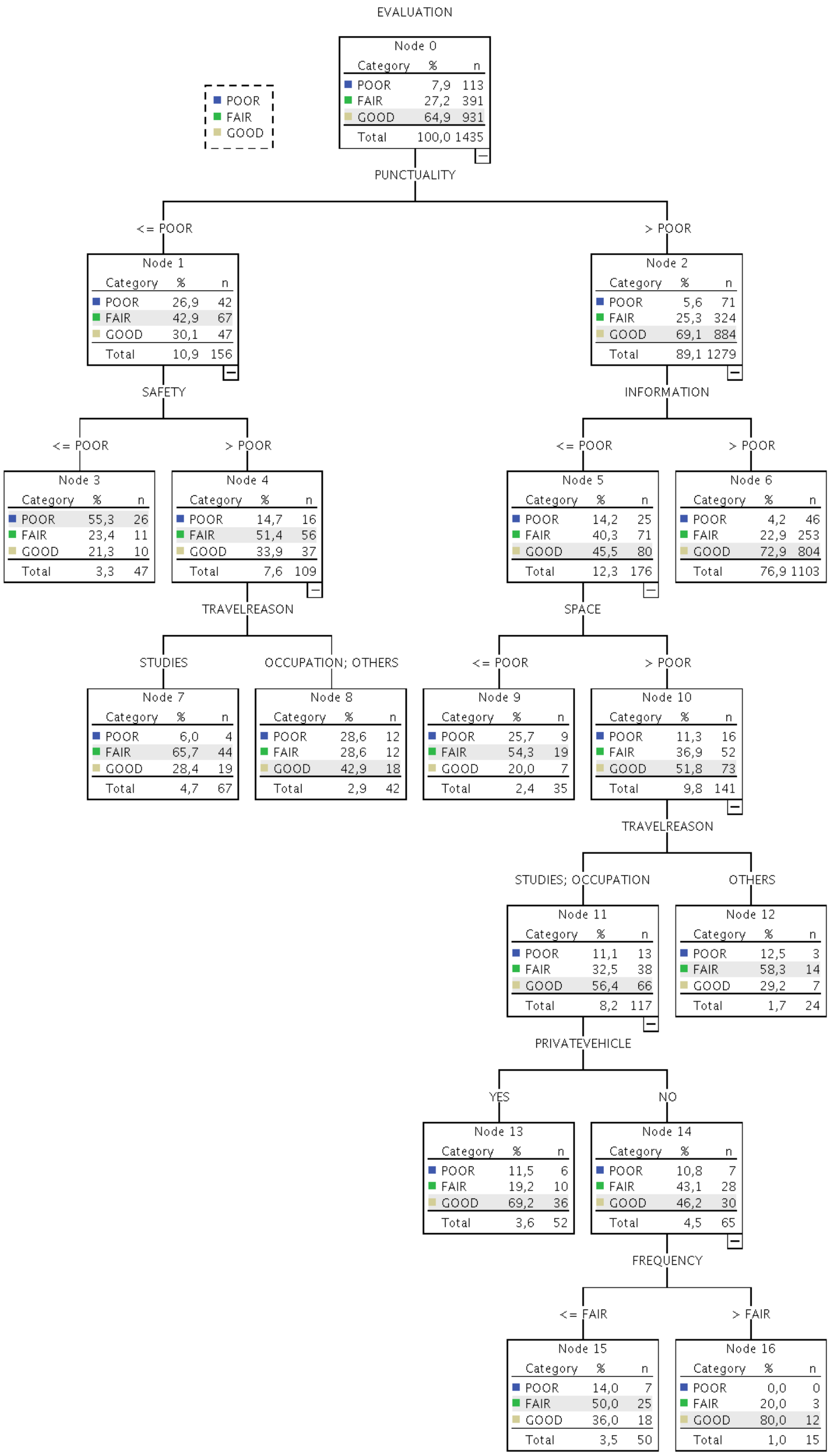


**Figure 3. CART built for the Cluster 1**

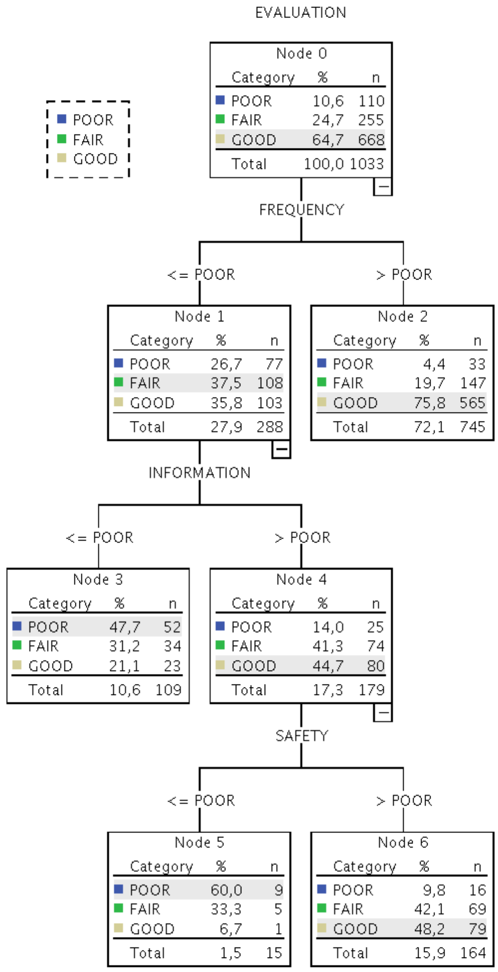


**Figure 4. CART built for the Cluster 2**

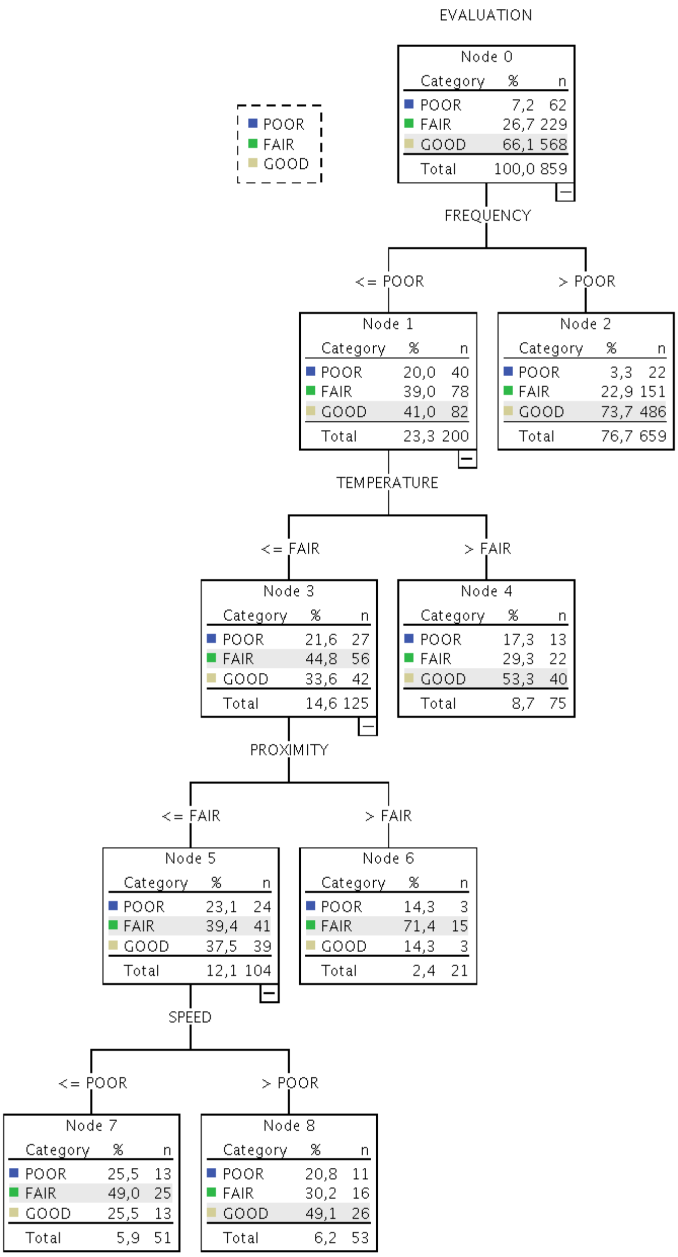


**Figure 5. CART built for Cluster 3**

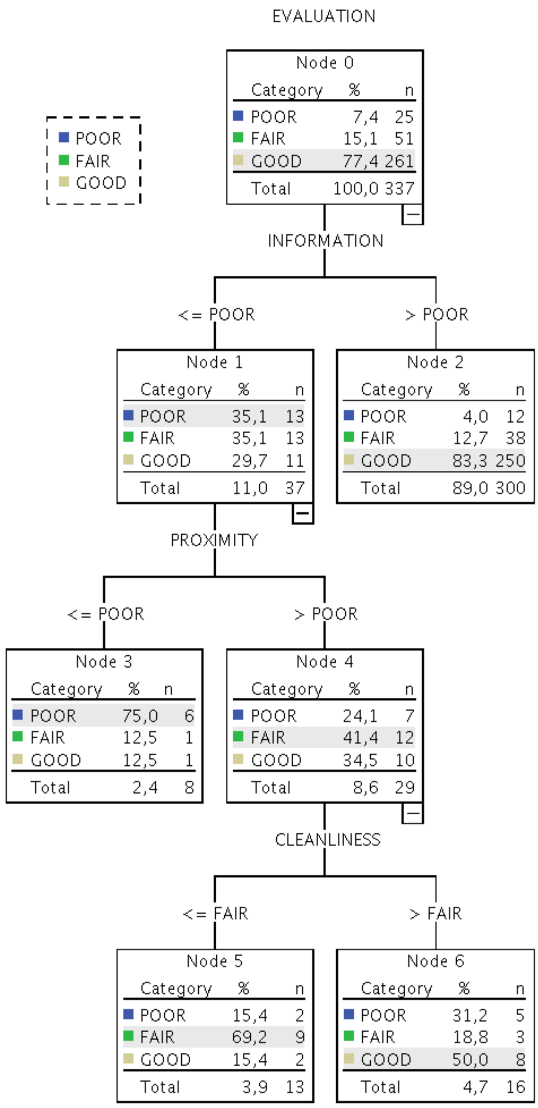


**Figure 6. CART built for the Cluster 4**

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 output is one of the most valuable of those provided by CART analysis. This information is obtained for all the independent variables and serves to identify 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 the 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 toward bus transit services in Belfast 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 toward the service (potential users). Thus, public transport planners would do wisely to focus on this service aspect to achieve a behavioural 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 travellers 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"). Information 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, and so on. For this reason they need simple yet adequate information about the service, and this information often has to be complemented with driver responses. This is why employee courtesy 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 that often generate delays. Additionally, Safety is a key factor for frequent passengers. While for the “Young students” of Cluster 1 Information and Safety constitute the most important service characteristics, for the “Working women” of Cluster 2 a large group of variables exerts a noteworthy influence on overall service quality evaluation, perhaps because they are non-captive users of the bus service who consider many characteristics before making 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 tend to 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 to become more familiar with passenger preferences and needs regarding service. Such knowledge helps transport planners develop personalized marketing rather than generalized interventions. In fact, the real factors that are important for passengers may be masked when they are analyzed as a whole.

According to these results, some degree of personalized marketing could be initiated 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 concerning the service frequency, comparative information regarding travel times using the car versus the bus service, assessment of the time wasted in traffic jams or needed to locate, for example, parking spaces, maps with bus stop locations, parking areas near the bus network, shopping, hospital and business areas, 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 using cluster analysis and decision tree techniques. Data were taken from various customer satisfaction surveys carried out over the period 2008-2011. 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 now able to develop specific personalized marketing strategies. As such personalization improves passenger satisfaction and loyalty, this information will serve 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 the field of public transport service quality, by considering various socioeconomic characteristics of the users and their travel habits simultaneously. Detailed profiles of users that have more homogeneous opinions about the service were discerned. This stratification will help public transport managers to better understand passenger behaviour 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 service quality, 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 passenger profiles—specifically, the passengers' various 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, likely 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 prominent variables from the overall evaluation differed substantially.

Several 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 these variables 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 influencing their modal choice;
- Information has substantial impact on frequent passengers' evaluations (Clusters 1 and 2), while 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 while passenger opinion on the whole is heterogeneous, the personalized analysis is a successful approach for identifying needs and requirements to detect specific patterns among the service characteristics (following the path of the decision trees) as well as the extent of association that certain variables have with different user profiles. Information and details arising from service quality evaluations can be masked when 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, 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 recouped quickly. 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 thus 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 study cannot be extrapolated to other regions or other public transport (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. While these results should not be extrapolated to other regions, or types of PT services, it can be concluded that the latent class cluster methodology represents a powerful and suitable tool for extracting specific profiles of passengers. This approach permits public transport managers to understand passenger behaviour better through familiarization with their profiles and through implementation of specific campaigns and better oriented system management in terms of the perceived service quality of different user groups. This work demonstrates how it is possible to identify specific passenger profiles in a transit service to perform more efficient personalized marketing. However, it is uncommon for a typical operator to be able to apply the proposed methodology without advanced statistical knowledge. Nevertheless, given that most services subcontract to a specialized company to conduct the survey and to analyse the data, it still benefits operators to know of the advantages of this method against the traditional ones to motivate charging the specialized companies with the task of developing this sort of analysis.

Finally, DT methodology has several advantages inherent to non-parametric models, as it does not require prior probabilistic knowledge of the study phenomena and as there are no model assumptions or predefined underlying relationships between variables. Several 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 the appropriate strategy in light 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; furthermore, 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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