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ABSTRACT

Existing approaches dealing with customer perception data have two fundamental challenges: heterogeneity of customer perceptions and simultaneous interrelationships between attitudes that explain customer behavior. This paper aims to provide practitioners with a methodology to address the twin challengers of service quality evaluation based on public transit user behavioral theory and advanced market segmentation. The original contributions of this paper are: the definition of customer typologies based on advanced customer segmentation with Latent Class Clustering; analysis of the effect of service quality perceptions on behavioral intentions within the behavioral theory framework that considers multiple attitudes simultaneously affecting customer intentions; identification of transit service improvement opportunities aimed at most customers as well as for specific customer typologies. Our research shows practitioners and researchers that specific needs and perceptions of advanced segmentations of customers can be identified and they may be as important as those shared by most customers. We applied our methodology to a light rail transit service in Seville, Spain. We measured the direct effect of LRT service quality on behavioral intentions, customer satisfaction and, in the case of some customers, the available transport alternatives. Other observed attitudes of customers were also indirectly related to behavioral intentions. We found common customer agreement about aspects of LRT service quality for tangible service equipment, accessibility, information, individual space and environmental pollution. Customers clearly showed different opinions relating to safety, customer services and availability.

Keywords: light rail transit; market segmentation; quality of service; cluster analysis; importance-performance analysis; structural equation model

1. INTRODUCTION

The quality of public transport can be a key determinant on user behavior (Cascetta and Carteni, 2014), and consequently it has become one of the main priorities of sustainable transport policies. Providing a quality of the service that is highly thought of by its customers can encourage the use of alternative modes of transport to the private car and allow for a more efficient use of public space as well as reduce the environmental impact of transportation (European Commission, 2007). Furthermore, according to the Handbook for Measuring Customer Satisfaction and Service Quality (Transportation Research Record, 1999), the improvement of customer satisfaction (CS) can benefit public transport (PT) agencies by increasing transit ridership of current and new customers and the improvement of the public image.

The importance of customer perceptions of transit service quality and their levels of satisfaction have motivated numerous attempts by researchers and practitioners to promote service quality improvements based on customer perception data. However, two fundamental challenges to these approaches remained unresolved: the heterogeneous nature of customer perceptions and the simultaneous relationships between different components of customer perception described in behavioral theory.

The effectiveness of soft transport policies (e.g., marketing strategies) depends on whether or not the heterogeneity of customers is taken into account and if improvement measures are tailored to different typologies of customer (Daniels and Mulley, 2013; Bamberg et al., 2011; Dell'Olio et al., 2010). Researchers often deal with heterogeneity by segmenting data into broad customer categories. Many authors have focused their studies on gender (de Oña and de Oña, 2015; Schrover et al, 2007), age (de Oña and de Oña, 2015; Hine and Scott, 2000) and employment status (e.g., employee, retired, student) (Daniels and Mulley, 2013). However, these approaches have limitations such as the possible under representation of certain customer categories in the case of reduced sample size (de Oña et al., 2013) which can lead to practitioners overlooking the specific needs and expectations of their customers (Van Lierop and El-Geneidy, 2015). Other more complex procedures have also been used, for analyzing this heterogeneity, such as discrete choice models with random parameters (e.g., Bordagaray et al., 2014) or advance stratification techniques. The analysis of transit customer perception using advanced stratification techniques in the field of Data Mining (e.g. Cluster Analysis) is scarce despite their successful application in this context. Van Lierop and El-Geneidy (2015) demonstrated the potential of this approach by using a K-means Cluster Analysis to define more flexible market segments that can be found in different PT services, and de Oña, de Oña and López (2015) applied Cluster Analysis to a metropolitan bus service to identify different customer profiles. Furthermore, most multivariate analysis techniques used to study customer perceptions allow researchers to look into only one relationship at a time, thus limiting the ability of the analysis to answer a series of simultaneous questions characterizing the behavioral theory of public transit customers (Hair et al., 2010).

The motivation of this paper is to further research into how to overcome the difficulties mentioned above within the existing framework of public transit customer behavioral theory. Our focus is to develop an analytical method through the integrated use of Latent Class Clustering and Structural Equation Modeling (SEM) that combined with Importance-Performance Analysis (IPA) allows us to investigate the behavioral theory framework of public transit customers and identify general and customer-specific service quality improvements to increase ridership. This paper also introduces an application of our method with a non-experimental analysis of the perceptions about service quality and attitudes towards the service of a sample of 3,198 customers of a light rail transit service (LRT) in Seville, Spain.

The rest of the paper is organized as follows: the Behavioral Theory Context section describes the existing framework of behavioral theory regarding public transit customers; the Methodology section introduces the proposed method with SEM, Latent Class Clustering and IPA; the Method Application section briefly describes the LRT service and the data collection; the Results and Discussion part summarizes the main results of a stratified analysis of PT customers´ evaluations of SQ and attitudes based on the proposed method, which is followed by a summary of the main Conclusions drawn from this research for the benefit of researchers and practitioners.

2. BEHAVIORAL THEORY CONTEXT

Customer loyalty is considered a major factor of a company's long-term financial performance and an important source of competitive advantage (Lam et al., 2004). Customer loyalty can be defined as "a deeply held commitment to repurchase or re-patronize a preferred product or service in the future" (Oliver, 1999), and it relates to favorable behavioral intentions towards the service (Lai and Chen, 2011). A substantial part of the literature in behavioral research that is focused on customer loyalty agrees that Service Quality (SQ) is the vehicle to Customer Satisfaction (CS) (Chen, 2008; Oliver, 2010; Chou and Kim, 2009) and that CS is the link between SQ and customer loyalty (Dabholkar et al., 2000; Chiou and Chen, 2012; Jen et al., 2011; De Oña et al., 2016). Furthermore, there are reported evidences of valid behavioral models in which SQ and CS have a determinant effect on customer loyalty for customers of high-speed rail services (Yilmaz and Ari, 2016; Jomnonkwao et al., 2015; Chou et al., 2014), bus and heavy-rail transit services (Tri-County Metropolitan Transportation District of Oregon, 1995; Minser and Webb, 2010) , as well as light-rail transit services (Lai and Chen, 2011; Tri-County Metropolitan Transportation District of Oregon, 1995; de Oña et al., 2015). Additionally, other perceptions of passengers such as involvement with PT, the perceived value of the service, the experience of service disruptions, the switching costs and the public image may have a notable role to play for customers of PT (Lai and Chen, 2011; Zhao et al., 2014; Carrel et al., 2013; Jen et al., 2011; Yilmaz and Ari, 2016).

The behavioral theory framework of customer perceptions introduced above is useful to address current concerns in the PT sector to improve SQ and make PT more attractive to its customers (Lai and Chen, 2011; Shen and Li, 2014). With this regard, there are two different types of transport policies that aim to reduce private car use: "Hard" transport and "Soft" transport policies (Bamberg et al., 2011). The former are related to changes in the objective environment such as improvements to infrastructure and the management of PT services, along with increased costs for car use. On the other hand, "Soft" transport policies are focused on car user decision making, and aim to encourage the use of alternative modes of transport by altering customer perceptions of the objective environment and their judgments about different travel options. Such measures commonly consist of workplace or school travel plans, personalized travel planning, marketing of PT and travel awareness campaigns. Additionally, there is a growing interest in soft transport policies because empirical evidence exists showing that policies such as marketing campaigns are cost-effective strategies to increase transit ridership (Bamberg et al., 2011; Currie and Wallis, 2008), whereas hard transport policies are difficult to implement and may not be effective on their own (Bamberg et al., 2011).

3. METHODOLOGY

The method presented here is based on behavioral theory and deals with the heterogeneity and interrelationships in perception data. This is achieved through the integrated use of Latent Class Clustering and SEM that in combination with IPA allow us to identify effective general and customer-specific service improvement to enhance ridership. The three components of our method and process are represented in Figure 1. Firstly, advanced market segmentation is performed with Latent Class Clustering to identify profiles of PT customers based on socio-demographic characteristics, travel needs and SQ perceptions. Secondly, we construct and test the behavioral theory underpinning PT customers' decisions with SEM. This step allows us to assess the robustness of the scales created to measure customer perceptions. The strength of the relationship between service quality features and other customer attitudes with their behavioral intention to reuse the service is also assessed in this step. Lastly, the service performance results of the previous two steps are used in the IPA, which allows for a customer-specific analysis of service quality improvement measures. The following three

Methodology subsections will further explain the three components of our method introduced above and represented in Figure 1.

(Figure 1)

3.1. Cluster Analysis

Cluster Analysis is based on heuristics that try to maximize the similarity between elements within a group (cluster) and get the maximum difference between elements of different groups (Fraley and Raftery, 2002). Latent Class Clustering is considered to be the most appropriate technique for conducting Cluster Analysis as it provides several advantages (Hair et al., 2010; Magidson and Vermunt, 2002; Vermunt and Magidson, 2005): the simultaneous consideration of different types of variables (continual, ordinal and nominal) and the normalization of variables does not affect the solutions of the clusters. We refer the reader to de Oña et al. (2013) for a detailed description.

A 4-step methodology was followed to define the variables and to determine the number of clusters in the solution:

- Step 1: Selection of variables to be considered in the Latent Class Clustering.
- Step 2: Identification of the best solution, based on a competing model strategy that compared ten possible Latent Class Clustering solutions that respectively had from 1 to 10 as the number of clusters to be modeled. A test of statistical significance (Wald test, $p<0.05$) was used to condense the number of explanatory variables originally considered in the Latent Class Clustering. If a variable was not statistically significant in any of the ten possible solutions it was no longer considered as an explanatory variable. However, before a variable was definitely excluded from the analysis, its possible role as a covariate was considered with a Wald test. Finally, the best solution (number of clusters) was chosen by considering criterions of Information, Structural Simplicity, Parsimony and Representation.

- Step 3: Development of the Latent Class Model. As in the previous step, a process of variable condensation was applied to the best solution, and the goodness-of-fit indices of the final solution were evaluated.
- Step 4: Once the Latent Class Model is considered to be satisfactory, the different clusters are used to identify and characterize typologies of customers.

Four criterions of information were considered: Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), the Consistent Akaike Information Criterion (CAIC) and the Parsimonious Criterion. The Parsimonious criterion considers that a model is acceptable if it achieves marginal improvements in goodness-of-fits greater than 1%. If possible, a model that allows the best goodness-of-fit but also a lesser number of clusters is preferred. Lastly, the best Latent Class Model should consist of clusters with over-represented categories of customers that make the characterization of customer typologies easier.

3.2. Structural Equation Modeling

SEM allows researchers to explain the relationships among multiple variables by examining the structure of interrelationships expressed in a series of equations. SEM examines more than one relationship at a time making it a technique to test a set of hypotheses that considers all the available information (Hair et al., 2010).

SEM consists of two components: a measurement model that assesses unobserved latent variables (or constructs) as linear functions of observed variables (items), and a structural model that shows the direction and strengths of the relationships of the latent variables. The relationships construct-item and construct-construct are associated to a standardized factor loading (or standardized regression weight, SRW, using AMOS software package terminology) that indicates the strength and significance of the relationship.

The Maximum likelihood method was used to estimate the model´s parameters (Golob, 2003). The soundness of the measurement model can be evaluated by conducting a Confirmatory Factor Analysis that allows looking into its Construct Validity and goodness-of-fit. Convergent Validity is a condition for Construct Validity and indicates that the items related to a construct converge or share a high proportion of variance in common. Convergent Validity can be assumed to be satisfactory if the SRW of the items that are related to a construct are statistically significant and ideally higher than 0.7. Furthermore, Reliability is also an indicator of convergent validity and can be assessed by looking at Construct Reliability scores (CRE), which indicate a good reliability if they show values of 0.7 or higher (Hair et al., 2010). Similarly, how well the structural model fits the data can be tested by analyzing goodness-of-fit indices such as the chi-squared/degrees of freedom, the goodness of fit index (GFI), the root mean square error of approximation (RMSEA) and the comparative fit index (CFI) (Chou et al., 2014).

SEM was used to test the theory underpinning a behavioral model of public transit customers that was chosen after a thorough literature review. This paper builds on a previous study (de Oña et al., 2015) in which the reader can find a detailed description of the methodology used to develop the questionnaire.

The behavioral model with the passengers of this LRT service consisted of six constructs related to the perceptions and attitudes of customers towards the service. The hypothesized structural relationships between these six constructs is represented in Figure 2 and further described as follows:

- *Behavioral Intention (BI):* Customers´ favorable BI toward the service that defines customer loyalty (i.e. willingness to re-use the service and recommend it to others).
- *Service Quality (SQ):* this is a cognitive judgment and thus and antecedent of CS (Oliver, 2010). Eight dimensions define SQ: SQ1. *Tangible Service Equipment*, SQ2. *Accessibility*, SQ3.

Availability of the Service, SQ4. *Customer Service*, SQ5. *Safety*, SQ6. *Information*, SQ7. *Environmental Pollution* and SQ8. *Individual Space*. Additionally, the item SQ9. *Overall Service Quality* was also used to measure SQ (de Oña et al., 2015).

- *Customer Satisfaction (CS):* is an affective judgment based on the experience of customers using the service and links SQ with BI.
- *Perceived Costs (PC)* and *Perceived Benefits (PB):* they refer to the cost-benefit analysis that compares customer choices between different transportation alternatives (Jen et al., 2012). They relate to monetary and non-monetary aspects that the customer can lose or win by choosing one transport option against another.
- *Involvement with Public Transit (INV):* corresponds to the level of interest in or importance of PT for the customer (Lai and Chen, 2011) and it could affect SQ perceptions, satisfaction and the perceived value of the service.
- *Attractive Alternatives (AA):* The hypothesis underpinning the behavioral theory focused on customer loyalty considers that customers choose a transport mode between different options (Zhao et al., 2014), and thus the available alternatives might have an effect on their behavior.

(Figure 2)

Moreover, the variables showed in Table 1 and Table 2 formed the SEM measurement model, that is, the scales used to measure perceptions related to the six constructs introduced above. Note that to measure the construct of SQ we used a two-level measurement model in which SQ is measured by eight SQ constructs in addition to the variable describing overall customer perception of SQ. For the sake of clarity, the scales used to measure SQ are separated in Table 1.

(Table 1)

(Table 2)

3.3. Importance-Performance Analysis

Practitioners often use Importance-Performance Analysis (IPA) to study customer perceptions of the service attributes. By conducting an average split based on importance and performance outcomes, the attributes of a service can show an upper-average/under-average importance and performance in regards to SQ. Based on these levels, the attributes can be classified into four labels or quadrants represented on a scatterplot: "Keep up the good work" (upper-average importance and performance), "Possible overkill" (upper-average performance, under-average importance), "Concentrate here" (upper-average importance, under-average performance) and "Lower priority" (under-average importance and performance).

Our method includes the outcomes of the eight SQ dimensions from SEM results. The importance of each SQ dimension is equivalent to the SRW between SQ and the dimensions, respectively. Their performance score can be estimated as the average perceived SQ of the attributes that defined each of the eight SQ dimensions.

4. Method application to a light rail transit service

The application of our analytical method focuses on the Metro of Seville (Spain), a 1-line partially underground LRT that carried 13.7 million passengers in 2013. The length of the line is 18 kilometers with 21 stations. This LRT line connects four municipalities in the metropolitan area of Seville that together register a population of 850,000 inhabitants. Based on the most recent available data about regional mobility in 2007, the modal share of all trips in Seville was 53.9% by car or motorcycle, 10.4% by public transit and 35.7% by walking or bicycle (OMM, 2016). This public transport service carried 13.7 million passengers in 2013.

Passenger perceptions of SQ and attitudes towards the LRT were collected with an on-line survey. It gathered information relating to customer attitudes towards the LRT (Part A), perceptions about the SQ (Part B), travel habits (Part C) and socio-demographic characteristics (Part D).

In Part B, respondents were asked for their SQ evaluation in regards to the overall LRT service and 37 of its attributes. Similarly, respondents answered 26 questions related to their attitudes towards the LRT service (Part A) described above. All the questions in Part A and B were measured with an 11 point numeric scale, which in Part A referred to the level of agreement (0-totally disagree and 10-totally agree) and in Part B referred to the level of SQ (0-lowest quality and 10-highest quality). Only one question relating to the overall satisfaction of the passenger with the service was measured with a 5-point Likert scale (1-lowest level of satisfaction, 5-highest level of satisfaction).

19,863 cards were distributed to customers by trained interviewers during a period of two weeks (May-June 2014), on weekdays, Saturdays and Sundays. A raffle of two electronic devices was held as a reward for participants who completed the survey. 3,365 responses were registered (response rate value of 17.09%), from which 3,198 were valid for subsequent analysis using the method introduced above. Table 2 and Table 3 summarize the socio-economic characteristics and travel habits of the complete sample, respectively. These tables also include the same characteristics of the six clusters that resulted after applying our method and that will be further explained in the following section dealing with Results and Discussion.

(Table 3)

(Table 4)

5. RESULTS AND DISCUSSION

5.1. Definition of customer typologies

The best Latent Class Model was obtained by following the 4-step process previously introduced in the corresponding Methodology section. The best solution consisted of six clusters and 31 explanatory variables from parts C and D of the survey, and overall customer SQ. Table 3 and Table 4 show these 31 explanatory variables and their group response rates (the response categories of variables C1 and D3 were considered as independent dichotomous variables for the cluster analysis).

Based on Information and Parsimonious Criterions, the best solution would have been a Latent Class Model with five clusters (marginal goodness-of-fit improvements: 0.33% of BIC, 0.59% of AIC and 0.29% of CAIC). However, a sensitivity analysis with Latent Class Model solutions of four and six clusters revealed that a Latent Class Model with six clusters would significantly improve the representativeness of the customer typologies.

A comparison of the response group characteristics of each cluster with the complete sample allows us to characterize the customer typology in each cluster based on over-represented response categories. Specifically, in the case where a cluster showed a response category with a relative frequency equal to or greater than 1.3 times the corresponding relative frequency of the complete sample, this response category was considered over-represented in that cluster. Furthermore, in the case that this proportion was equal to or greater than 1.5, the response category was considered to be strongly over-represented in that cluster.

- **Cluster 1** –*"Non-student users with high income and with a predisposition to use the private car".* In this Cluster, customers in the age range 26 to 65 are over-represented. The majority of them have completed a Bachelors or an even higher education degree and are currently employed. They can use their own private car for their main trip purpose of travelling to their job. However, the categories of lack of parking, traffic jam and private vehicle not available are over-represented reasons to use the LRT in this group. Furthermore, the high household monthly income (>2,401€) is also highlighted. Therefore, Cluster 1 consists of over-represented employees of a working age of around 26 years old which is a common age for finishing university studies in Spain. They therefore, have high a high standard of education and income level. The main reasons to use the metro for getting to work are the lack of parking, traffic jams (common problems in big cities at peak hours) and, to a lesser degree, the non availability of their private vehicle.

- **Cluster 2** – *"Non-student users and high income users with a predisposition to use the metro".* Customers over 26 years old are over-represented in this Cluster along with customers over 66 years old, which is the difference with Cluster 1. As in Cluster 1, customers have Bachelor degrees or higher and have high household monthly incomes. The employed respondents are over-represented as are retired people, because of the proportion of customers over 66 years old. They can either use their own private vehicle or the LRT service to travel to work, to leisure activities or to other destinations. Nevertheless, the principal distinctive characteristic of this cluster when compared to Cluster 1 is that these customers choose the LRT service instead of their own private vehicle due to its price, comfort and speed. This typology of customers also showed the highest overall satisfaction with the SQ of the LRT service. To summarize, in this cluster employed and retired customers who have finished higher education and earn high incomes are over-represented. They have the possibility to use their own private vehicle to go work, leisure activities or other destinations but they prefer to use the LRT service due to its price, comfort and speed.

- **Cluster 3–** *"Captive and non-driver teenagers and university students".* This Cluster has an over-representation of customers under 26 years old and their employment status is they are students. They have only completed High School or Secondary School which means this cluster refers to teenagers who attend high school or younger people who are at the university. They do not possess driving licenses and the LRT service is shown as their only way of making a journey for the purpose of education, thus, they can be called captive customers (they don't have another alternative mode of transportation other than the LRT for their journey). In other words, this Cluster is formed of teenagers and university students who, in order to go to University/School, have to use the LRT service because they do not have any other options.

- **Cluster 4**– *"Captive and driver university students who are critical of the metro".* As opposed to Cluster 3 where customers aged between 18 and 25 years old are over-represented and students with high school or professional education are highlighted, only university students are represented in cluster 4. Another difference is that the customers represented by this cluster possess a driving license but most do not have access to a private car, so they prefer to use the LRT service to travel to university as this is their only real alternative, which makes them captive. This cluster showed the lowest overall score for the SQ of the LRT. To summarize, this Cluster is formed of University students who use the LRT service to travel to university as they have no other choice although they have a driving license and a small minority have access to a private car.

- **Cluster 5** – *"Non-captive university students".* This cluster is formed of over-represented customers between 18 and 25 years old, who have a high school or professional education degree and currently study. Therefore, the customers in this cluster can be considered as university students. Although they have a driving license, the main difference with Cluster 4 is that they are non-captive (they have an alternative mode of transport other than the LRT for making their trip) and their most frequent reasons to use the LRT services are lack of parking, traffic jam and the private vehicle is not available. In conclusion, this cluster is formed by university students who use the LRT service to go to their university and are non-captive, but, they use the LRT service due to the lack of parking, traffic jams and/or their private vehicle is not available at the time.

- **Cluster 6**– *"Low income customers with a high predisposition to use PT*". In this cluster the over-represented customers were aged between 26 and over 66 years and had a diverse educational background from no qualifications to university or above. In terms of occupation status, the over-represented customers are employed or have another occupation and, to a lesser degree, are retired. The lack of a driving license and lack of access to a private car are over-represented reasons to use the LRT in this cluster, and they are the second and third most frequent reasons after travel time. These customers mainly used the LRT service to travel to work and, to a lesser degree, leisure activities and/or other reasons. Low income customers (< 1,201 €) are also over-represented. In addition, they showed a relatively higher average perception of the overall SQ. Therefore, this cluster is formed by low income customers, they are working or, to a lesser degree, retired, and they have to use the LRT service to travel to work or leisure activities because they lack a driving license or access to a private vehicle. However, they perceived the quality of the LRT service as high.

5.2. A robust scale to measure customer perceptions

A Confirmatory Factor Analysis allowed us to look into the validity of the measurement models with the complete sample and the six clusters (Ci, i=1,…,6). The Confirmatory Factor Analysis was based on the significance of SRW and Construct Reliability scores, and allowed us to simultaneously test the postulated measurement models of the seven constructs (Figure 2) with the complete sample and with each cluster. The SEM measurement models were refined based on Confirmatory Factor Analysis results by stepwise deleting a total of five items that showed a low level of significance in regard to the latent construct that they were measuring. The results of the SEM measurement models with the complete sample and six clusters can be found in Table 5 and Table 6.

Furthermore, the measurement model of the construct *Attractive Alternatives* only showed satisfactory results in the case of C2. In that case, SRW were significant and showed the correct sign, although construct reliability was low (CR=0.55). Therefore, this construct was only included in the model with C2 because of its relevance to this study. Finally, the Confirmatory Factor Analysis models fitted the data to an acceptable degree based on the goodness-of-fit indices (RMSEA<0.08; CFI>0.9 and GFI>0.9).

(Table 5)

(Table 6)

5.3. Customer-specific SEM structural models

The results of the seven SEM structural models (complete sample and six clusters) are summarized in Table 7. The seven models showed an acceptable goodness-of-fit: according to Hair et al. (2010), ratios of 3:1 for the normalized chi-squared are associated with good fitting models, except in circumstances with larger sample sizes (over 750). In our case, all models with a sample size of less than 750 showed a normalized chi-squared of 3:1 or less, which indicates good fitting models. RMSEA always showed values within the recommended threshold, and CFI was also close to the recommended value of 0.9. On the other hand, GFI showed values slightly under the recommended threshold of 0.9. Furthermore, all significant structural relationships showed the correct sign, providing evidence for the majority of relationships hypothesized in the behavioral model of customers of this particular LRT service (Figure 2). Some of the goodness-of-fit parameters are not within the ideal thresholds documented in the literature, which are highly difficult to achieve in practice, but we considered these values to be in the order of other recognized published work (Acker and Witlox, 2010). Therefore, the level of goodness-of-fit of the seven models was considered sufficient for the purposes of this study and the remarkable differences found between the models are discussed below.

Based on the results of the structural model (Table 7), only the customers in C2 showed evidence that the available transportation alternatives to the LRT service were actually attractive for them and had a negative effect on their *Behavioral Intention* (-0.209). In fact, C2's passengers commonly made trips under 25 min (87.2%) and, compared to the general trend of the complete sample, they more frequently had the possibility of making that trip by foot, motorcycle or tram (Table 4). On the other hand, the passengers in C1 and C5 were the typology of users that most frequently preferred the car as an alternative transport mode (58.6% and 49.7%, respectively). However, the private vehicle might not have been an attractive alternative mode to the LRT service because of the existing drawbacks to its use (i.e., lack of parking and congestion) that they experienced more often than the other clusters and the overall sample (Table 4). Moreover, the alternatives for C3 and C4 must not have been overly attractive because, when compared to the general trend of LRT customers, they were more predominantly captives of the LRT service (33% and 30.1%, respectively) and did not have a private vehicle (46.4% and 53.4%, respectively). Finally, C6 showed a relatively higher availability of alternative public transportation modes to the LRT (i.e., urban bus, metropolitan bus and tram) than the overall sample, which cannot have been sufficiently attractive to significantly affect their behavioral intentions towards the LRT service.

Furthermore, C2 and C6 were the only typologies of customer that showed a significant positive effect of *Involvement with PT* on CS (Table 7). This could be related to the fact that both clusters showed the highest average overall SQ perception (8.3 and 7.7, respectively) and most homogeneous opinions with this regard (standard deviation: 1.1 and 1.4, respectively). This finding is highly interesting because it can be argued that high levels of involvement strengthen the experience of emotions and more specifically positive emotions which, in this case, could have enhanced the affective component of customer satisfaction (Bloemer and Ruyter, 1999).

5.4. Identification of service quality improvement measures

An IPA based on the SEM results of each of the six clusters and the overall sample allowed us to identify general improvement measures which are applicable to all clusters as well as customer-specific improvement measures for certain typologies of users. Our IPA results are represented in **Figure 3** and are further explained below.

(Figure 3)

5.4.1. General measures

Acting on common trends across clusters could positively affect the maximum number of PT customers. IPA results (Figure 3) showed that trends common to all clusters were also found in the IPA results with the overall sample.

Firstly, the dimensions *Tangible Service Equipment*, *Accessibility* and *Information* were clearly classified as "Keep up the good work" factors due to their higher performance and weighting in the overall perceived SQ. This might be because the LRT is a new service (it came into operation in 2009): every station is provided with escalators and elevators; the stations and vehicles offer updated and reliable information; ticket validators and vending machines work properly, as do lighting and information panels. Therefore, there is agreement in regard to these three dimensions among the six clusters.

Special attention should generally be paid to the attributes that could worsen the quality assessment of the corresponding SQ dimension due to their relatively low perceived quality. In relation to the *Information*, the availability of up-to-date, simple and clear information in stations and on vehicles improved the perception of quality in relation to this SQ dimension (the corresponding attributes showed SQ≈7.8 and SRW≈0.8). On the other hand, the quality perception of information available through other media outlets (Internet, phone, mobile, etc.) (Attribute A31) lowers the quality assessment of this dimension (SQ=6.37; SRW=0.59).

Furthermore, the attributes relating to cleanliness and lighting (A1-A4), part of *Tangible Service Equipment*, showed notably high importance and SQ values (SQ≈8.25; SRW≈0.8). Conversely, temperature and appropriate driving aspects (A5 and A6, respectively) worsened the quality assessment of this dimension (SQ≈7.25; SRW≈0.59). The *Ease of access from the street to stations and platforms (A8)* tended to be really well valued and showed a high impact on *Accessibility* (SQ=8.15; SRW=0.8).

It is worth noting that *Availability of the Service* was affected by a really high quality assessment of *Punctuality (A18)* (SQ=8.49; SRW=0.74), however, customers commonly considered that the *Frequency (A13)* showed a relatively lower quality (SQ=7.29; SRW=0.69).

5.4.2. Customer-specific measures

In regard to the results of the IPA analysis, it is also possible to highlight some similarities and some peculiarities among the different customer profiles.

C1 is the typology of customers that perceived the worst level of quality in regards to the *Ease of connection between the LRT service with other transport modes (A12)* (SQ=7.09; SRW=0.57). These results could indicate that this typology of customers is misinformed due to a possible lack of information and their relatively more sporadic use of the LRT service (21.7%) (Table 2). Furthermore, this group of passengers showed the greatest proportion of customers holding a bachelor's or a higher education degree (66.6%), which could indicate greater awareness of the lack of information because higher education levels tend to induce more information acquisition (Chorus et al., 2010). This kind of customer could also be more aware of the difficulties around combining LRT with the private vehicle or other modes because they were the people that frequently drove to the LRT station at the start of their trip (45.8%) and from the final LRT station to their final destination (6.5%).

Individual space and *Environmental pollution* are classified as "Lower priority" factors among all clusters, although the SQ assessment of both dimensions varies with the customer typology. For example, C2 showed a higher score for both dimensions than the remaining clusters did (SQ=6.92 and SQ=7.12, respectively), which may be related to the higher predisposition of C2 to using PT. On the contrary, C4 and C5 had the lowest assessment for Individual Space and Environmental pollution. Moreover, C4 and C5 generally used the LRT service more frequently and they could therefore be more frequently exposed to crowds and uncomfortable situations. It is also worth noting that the generally minor influence of *Environmental pollution* on overall SQ (SRW<0.55) suggested that LRT customers in Seville had little awareness of the environmental impact of noise and vibration caused by the service.

Customer Service was classified as a "Concentrate here" factor in the case of C4. Customers from this cluster ("*Captive university students who are critical of the metro*") are more dissatisfied with all the attributes describing this factor than shown by the rest of the clusters. Differently to C4*, Customer service* was classified as "Possible Overkill" in the case of C1, C5 and C6.

In relation to the attributes of *Customer Service,* the quality level of *Performance of Customer Service (A22)* was commonly assessed as relatively low by all clusters. On the other hand, friendliness and the appearance of the staff (*A21* and *A23* respectively) was generally perceived as high quality. Therefore, in order to benefit from the *Customer Service* in the case of this LRT service, practitioners should pay special attention to information provision, and in particular, information relating to the intermodality of the PT service. The service could also make better use of the good appearance and friendliness of the staff.

Safety was classified as a "Concentrate here" factor in the case of C1, C4 and C5. For C5, *Safety* was placed on the threshold between "Concentrate here" and "Lower priority". These groups were mainly represented by high-income customers with a predisposition to use their cars, captive and non-captive university students, respectively. Specifically, C4 and C5 showed the worse assessment of this dimension (SQ=6.86 and SQ=6.91, respectively).

It is worth highlighting the relatively low evaluation of the level of quality in regards to *Sense of security against theft and aggression in stations and on vehicles* as a general trend (SQ=7.27; SRW= 0.74 for the overall sample). In fact, official reports about these types of aggressions indicate that the level of safety in the infrastructure of the LRT service is excellent, which may lead practitioners to derive biased conclusions from objective-based evaluations of SQ. Customers may encounter situations perceived as unsafe although these do not lead to any theft or aggression and are not officially reported. Public transport customers may also perceive the level of safety while using the LRT service associated to their complete journey (origin-destination). Therefore, if possible incidents happened nearby the LRT infrastructure when they accessed the stations such as park and ride lots, this could also affect their perception of the service's safety. In this regard, the importance of evaluating subjective measures of SQ relies on the identification of potential problems that undermine transit ridership and that are not captured by performance-based evaluations.

Finally, *Availability* was always shown to be highly important for customer perceptions (upper-average value) and in the cases of C4 and C5 it was classified as a "Concentrate here" factor showing a relatively worse assessment of its level of quality (SQ=7.11 and SQ=7.23 respectively). C4 and C5 considered *Waiting time on the platforms (A14)* and *Operating hours of the service (A16)* to have a lower level of quality. Moreover, *A16* represented a revealed weakness of this LRT service due to the lower-quality assessment (<6) common to all clusters except for C2.

6. CONCLUSIONS

The method developed and applied in this paper has shown that it is possible to identify transit service improvement needs based on customer perceptions while dealing with the heterogeneity and interrelationships found in perception data. Researchers often deal with heterogeneity by segmenting data into broader customer categories with the risk of constructing user typologies that are not homogenous and consequently overlook the specific needs and expectations of their customers. Furthermore, alternative multivariate techniques to SEM allow the researcher only to look into one relationship at a time, thus, limiting the ability of the analysis to answer a series of interrelated questions that characterize the behavioral theory of public transit customers. This research shows how to overcome these difficulties through the integrated use of cluster analysis and structural equation modeling that in combination with importance-performance analysis allows practitioners to identify general and customer-specific service improvement opportunities that affect behavioral intentions. Therefore, the proposed methodology results in the following original contributions:

- Distinct customer typologies may be required to analyze heterogeneous perceptions of transit service quality. Each typology should consist of a homogenous group of customers that at the same time differ from the other customer typologies based on demographic characteristics, travel habits and service quality evaluation. Latent Class Clustering is an appropriate tool to achieve this, which in our case allowed us to successfully define six customer typologies of the light rail transit service being analyzed.
- Behavioral intentions of customers do not only depend on their perception of service quality, but also on a series of factors related to their predisposition and intrinsic personal characteristics. Through structural equation modeling, we have shown eight direct structural interrelationships between concepts of customer perception including the effects of service quality, customer satisfaction and, in the case of some customers, the available transportation alternatives on their behavioral intentions. Perceived costs and benefits and involvement with public transportation are observed factors that are also indirectly related to behavioral intentions.

As a combination of the earlier two contributions, our research showed that it is possible to define service quality improvement measures around aspects of the service that bring consensus among customers, however, customer-specific measures are equally necessary to enhance overall perceived service quality and positive behavioral intentions. In the case of the light rail service studied in this research, we found agreement around tangible service equipment, accessibility, information, individual space and environmental pollution. Additionally, customers clearly showed different opinions relating to safety, customer service and availability.

A drawback of this research is that we did not attempt to extrapolate the findings of our sample to the general population of Seville or other transit services. Therefore, the identified customer typologies and service quality improvement measures have an ad-hoc nature. However, our method is replicable and underpinned by a considerable body of literature in behavioral modeling of transit customers; the authors would like to encourage the research community to use this method and contribute to the generalizability of possible frequent typologies of public transit customers and service quality factors that drive greater or lower levels of consensus among customers.

To conclude, this paper further develops soft transport policy measures by providing practitioners with a methodology for service quality evaluation and advanced market segmentation based on behavioral theory and its application to an LRT service.

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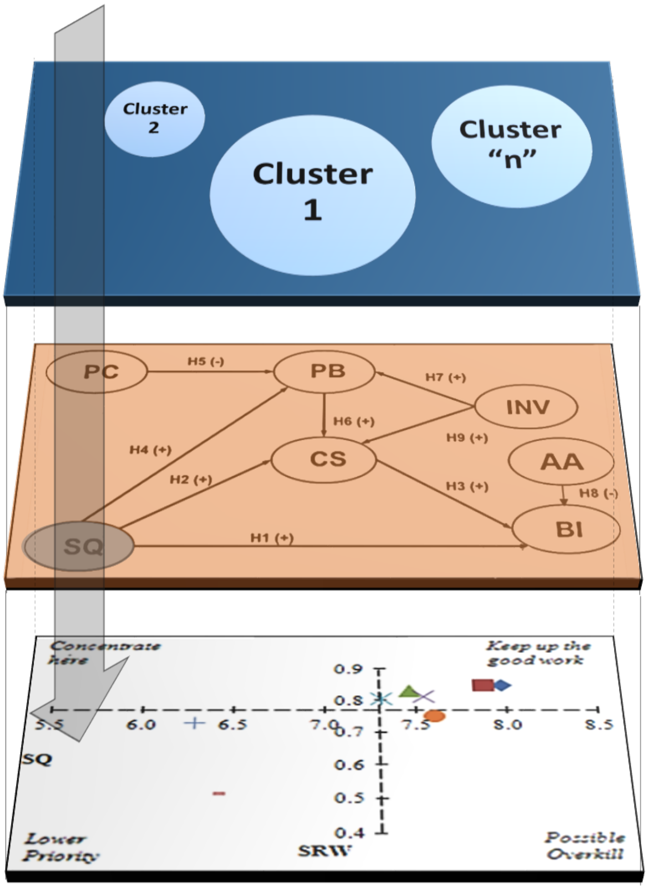


Cluster Analysis.
Definition of customer typologies.

Structural Equation Modeling.
Construction of scale to measure perceptions and customer-specific behavioral models.

Importance-Performance Analysis.
Definition of effective improvement measures from customer-specific analysis of perceptions.

Figure 1. Method for public transit service improvement based on customer perceptions

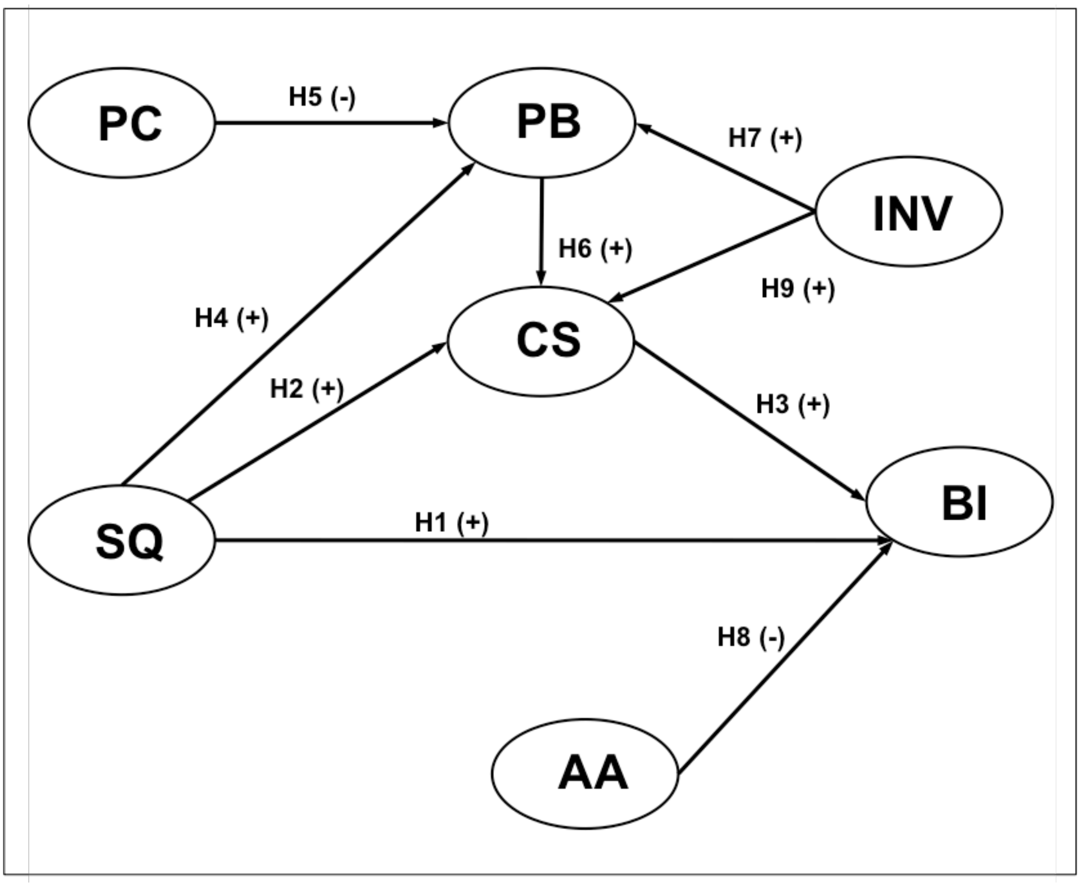
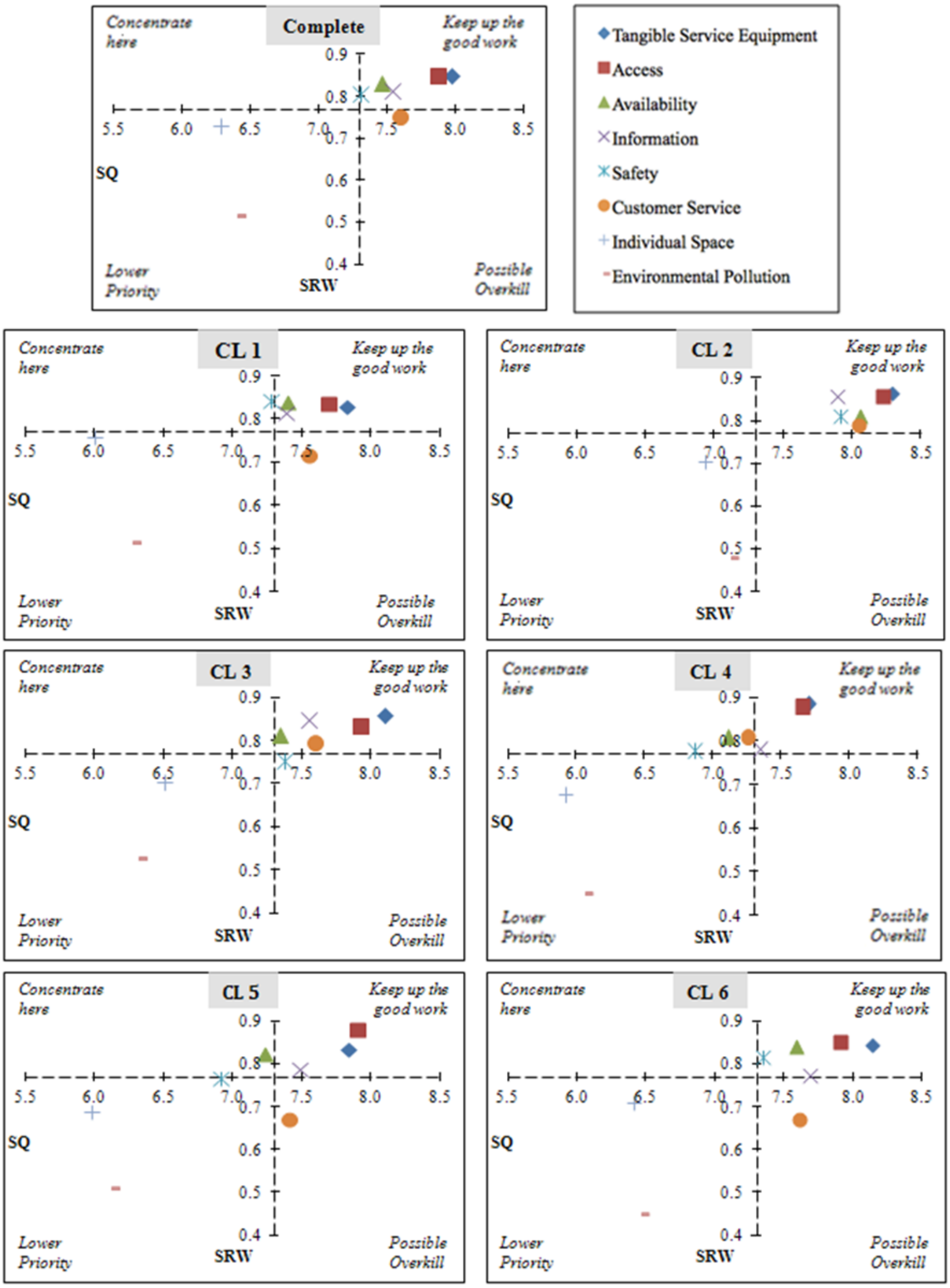


Figure 2. Conceptual behavioural model of public transport customers



Note: The reference values of importance and performance are calculated based on the results with the complete sample and they are also considered as the reference values to conduct the remaining IPA with the six clusters.

Figure 3. IPA results with complete sample and six clusters

TABLE 1.- Constructs used to measure service quality and corresponding attributes

Construct	Variable
SQ1. Tangible Service Equipment	A1. Cleanliness of the stations
	A2. Lighting in stations
	A3. Lighting on vehicles
	A4. Cleanliness of the vehicle
	A5. Temperature and ventilation system on vehicle and in stations
	A6. Appropriate driving
SQ2. Accessibility	A7. Ease of access for people with disabilities
	A8. Easy access to stations and platforms from the street
	A9. Operation of elevators, escalators, etc.
	A10. Operation of ticket validators at the entrance/exit of stations
	A11. Easy use of ticket vending machines
	A12. Easy connection with other transportation modes such as bike rental, taxis, buses, etc.
SQ3. Availability of the Service	A13. Number of trains per day (frequency of the service)
	A14. Waiting time on the platform
	A15. Speed of the trip
	A16. Operating hours of the service
	A17. Regularity of the service (absence of interruptions caused by breakdown or incidents)
	A18. Punctuality
	A19. Proximity of stations to origin/destination (n.s.)
SQ4. Customer Service	A20. Effectiveness and speed of employees to respond, give information and deal with user´s daily problems
	A21. Courtesy of the employees
	A22. Performance of the Customer Service (offices, web site, contact by phone, deal with complaints, etc.)
	A23. Appearance of employees
SQ5. Safety	A24. Sense of security against theft and aggression in stations and on vehicles
	A25. Sense of security against accidents while traveling (crash/vehicle derailment)
	A26. Sense of security against slipping, falling and accidents at vehicle doors and escalators.
	A27. Signage of emergency exist and extinguishers
SQ6. Information	A28. Updated, precise and reliable information in stations (price. operating hours. stops. service interruptions. etc.)
	A29. Updated, precise and reliable information on vehicles (operating hours, stops, service interruptions, etc.)
	A30. Clear and simple notice boards with info/directions in stations
	A31. Information available through other communication technologies (internet, phone, mobile applications, etc.)
SQ7. Environmental Pollution	A32. Noise level on the vehicle
	A33. Vibration level on the vehicle
	A34. Noise level in stations
SQ8. Individual Space	A35. Seat availability in stations and on platforms
	A36. Level of comfort on vehicle (enough room seating/standing up)
SQ9. Overall SQ	A37. Overall service quality of the LRT

TABLE 2.- Remaining attitude construct and corresponding attributes

Customer Satisfaction (CS)	CS1. Overall Satisfaction with the service of the LRT
	CS2. Traveling by LRT attracts me
	CS3. I feel comfortable traveling by LRT
	CS4. The service of LRT meets my expectations
Perceived Costs (PC)	PC1. I believe that the price is high.
	PC2. I believe that the ticket price exceeds the costs of the LRT (staff, electricity, maintenance, etc.)
	PC3. I consider the costs of traveling by LRT to be high (time, money and comfort).
	PC4. Stations are far away from origin and/or destination (n.s.)
	PC5. The waiting time at platforms is excessive (n.s.)
Perceived Benefits (PB)	PB1. The service of LRT is good
	PB2. I believe that the quality-price ratio is appropriate
	PB3. The attention to the costumer is good
	PB4. I like the LRT because of the speed of trip
	PB5. The timetable of the LRT service satisfies my needs (n.s.)
Attractive Alternatives (AA)	AA1. I believe that there are good alternatives of public transportation to the LRT (e.g. bus, taxi)
	AA2. I do not mind which transport mode to use if it meets my needs
	AA3. I think that other modes of transport (e.g. car, bus, taxi) offer more advantages than the LRT
Behavioural Intention (BI)	BI1. I will travel by LRT again under the same conditions (money, time and comfort)
	BI2. I usually recommend the LRT service to others
	BI3. Surely. I will use the LRT service again
Involvement with Public Transit (INV)	INV1. I feel that taking public transit is consistent with my lifestyle
	INV2. I feel that by taking PT I help to protect the environment
	INV3. I like others to know the fact that I take public transit
	INV4. I like people who take public transit
	INV5. Independently of trip purpose, I always prefer to travel by PT
	INV6. I believe that using PT affects people´s opinion about me (n.s.)

TABLE 3.- Part D. Socio-economic characteristics of complete sample and six clusters

Variable	**Complete**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Sample Size	3198	842	584	534	479	394	365
D1. Gender:							
Man	46.7	48.8	50.2	43.6	48.2	49.7	35.1
Woman	53.3	51.2	49.8	56.4	51.8	50.3	64.9
D3. Availability of:							
Driver License	75.0	**98.8**	**95.5**	**0.2**	99.6	97.5	39.7
Access to private car	54.7	**93.8**	**83.4**	**2.6**	**20.0**	**87.8**	4.4
Access to motorcycle	6.7	7.2	**11.0**	3.7	4.6	8.4	4.1
Access to bicycle	43.2	38.2	39.6	53.6	45.5	52.0	32.6
None	12.0	0.0	0.0	**43.8**	0.8	0.0	39.7
D4. Age							
<18	2.8	0.0	0.0	**16.5**	0.2	0.0	0.3
18-25	41.6	6.3	3.1	**78.1**	**89.1**	**92.6**	13.7
26-40	28.9	**44.9**	**47.1**	5.2	10.6	6.6	**45.5**
41-65	25.6	**47.5**	**47.3**	0.0	0.0	0.8	**38.1**
>66	1.0	1.3	**2.2**	0.0	0.0	0.0	**2.5**
No response	0.1	0.0	0.3	0.2	0.0	0.0	0.0
D5. Level of studies completed							
None or Secondary School	9.0	6.7	10.3	**14.6**	1.3	1.3	**22.7**
High School or Professional Education	42.0	26.1	23.3	**66.1**	**63.3**	**61.2**	24.4
Bachelors or higher	48.5	**66.6**	**65.6**	18.4	35.5	37.3	52.3
No response	0.6	0.6	0.9	0.9	0.0	0.3	0.5
D6. Employment Status							
Employed	43.7	**80.4**	**76.2**	0.2	3.5	2.3	**67.9**
Student	41.5	0.5	0.7	**96.8**	**90.4**	**92.6**	1.4
Retired	2.6	**3.6**	**6.3**	0.2	0.0	0.0	**3.8**
Other	12.2	15.6	**16.8**	2.8	6.1	5.1	**26.8**
D7. Household size							
<3	24.0	34.0	39.0	9.4	9.4	3.8	39.7
3-4	60.4	54.6	52.7	68.2	70.6	72.3	48.8
>4	15.5	11.4	8.2	22.5	20.0	23.9	11.5
D9. Household monthly income (*)							
<1.201	28.8	20.2	23.8	31.5	34.4	31.2	**42.7**
1,201-1,800	21.0	24.1	21.7	18.7	16.7	21.8	21.1
1,801-2,400	16.5	20.4	19.5	13.5	14.8	13.2	12.6
>2,401	16.0	**24.2**	**23.6**	9.9	9.2	10.4	8.5
No response	17.7	11.0	11.3	26.4	24.8	23.4	15.1

Note: Column headings indicate the corresponding sample (Complete sample, and clusters C1 to C6). (*) D9 was rejected as an explanatory variable and covariate in Step 2 of the Latent Class Clustering analysis, which could be due to great amount of missing information in regard to this socio-economic aspect of respondents (17.7% non-response). It is kept in this table for characterization of user typologies purposes. The magnitudes used to characterize the clusters are highlighted in bold.

TABLE 4. Overall SQ and Part C travel habits of complete sample and clusters

Variable	**Comple**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Average overall SQ (SD)	7.6 (1.5)	7.5 (1.6)	**8.3** (1.1)	7.6 (1.5)	**7.1** (1.5)	7.4 (1.5)	**7.7** (1.4)
C1. Why LRT for this trip?							
a. Price	10.2	7.6	**14.6**	10.7	7.1	13.2	9.0
b. Comfort	50.0	54.9	62.5	45.9	36.7	49.5	42.7
c. Speed	66.6	59.1	**84.2**	65.5	58.0	66.2	69.0
d. Frequency	28.9	22.6	28.9	32.2	26.7	36.5	33.2
e. No driver license	14.5	0.1	0.0	62.9	1.5	0.0	**33.2**
f. No private vehicle	23.1	1.8	3.4	**46.4**	**53.4**	2.3	**52.3**
g. My only alternative	13.6	3.2	1.0	**33.0**	**30.1**	7.1	14.5
h. Lack of parking	32.2	**57.6**	38.7	6.2	6.7	**59.4**	5.2
i. Traffic jam	24.8	**40.5**	27.4	8.1	7.3	**48.0**	6.8
j. Private vehicle not available	6.0	**8.0**	3.6	0.7	10.2	**10.7**	2.7
C2. Trip Purpose							
Work	35.5	**61.9**	**56.8**	2.8	4.8	4.1	**62.5**
Studies	38.9	5.3	4.3	**77.7**	**83.9**	**88.1**	2.7
Leisure	15.3	18.8	**21.1**	15.4	8.6	5.1	17.8
Other	10.3	**14.0**	**17.8**	4.1	2.7	2.8	**17.0**
C4. Origin-LRT station by:							
Walk	62.5	43.7	79.6	69.1	69.9	53.6	68.8
Bus	9.6	5.1	1.0	14.0	16.5	9.4	18.6
Car	22.3	**45.8**	17.0	10.5	3.3	35.3	4.7
Other	5.6	5.3	2.4	6.4	10.2	1.8	7.9
C5. Time origin-LRT station:							
< 5 min	60.5	45.4	91.1	57.5	55.3	63.7	54.0
5-10 min	19.0	**26.7**	8.0	18.0	18.8	18.8	21.1
>15min	20.5	**27.9**	0.9	24.5	25.9	17.5	24.9
C6. LRT station-Destination by:							
Walk	86.3	83.7	93.7	84.8	86.4	90.6	78.1
Bus	6.0	5.3	1.5	8.4	7.3	4.3	11.2
Car	4.2	6.5	2.9	3.9	1.7	5.1	3.3
Other	3.5	4.4	1.9	2.8	4.6	0.0	7.4
C7. LRT Time station-Destination							
< 5 min	43.3	26.2	70.7	39.7	37.4	61.4	32.1
5-10 min	30.1	34.2	26.0	31.6	35.7	21.1	27.1
>15min	26.6	**39.5**	3.3	28.7	26.9	17.5	40.8
C8. Time origin-destination:							
< 25 min	34.9	7.0	87.2	33.3	28.0	34.3	27.4
25-40 min	39.0	57.6	12.7	36.7	37.6	42.1	40.3
>40min	26.1	35.4	0.2	30.0	34.4	23.6	32.3
C9. Type of ticket							
1 day ticket	9.7	8.9	10.3	12.2	9.6	6.9	10.1
Bono	31.6	39.2	40.9	24.9	23.0	25.1	26.8
Transport Agency Card	58.8	51.9	48.8	62.9	67.4	68.0	63.0
C10. Frequency of use							
>4 days/week	52.0	43.5	42.3	59.4	59.9	66.0	51.2
3-4 days/week	17.9	17.2	15.2	17.2	21.1	18.3	20.5
1-2 days/week	13.7	17.6	17.5	11.6	10.9	6.3	13.2
Occasionally	16.4	**21.7**	**25.0**	11.8	8.1	9.4	15.1
C12. Alternative to LRT:							
Walking	3.7	1.8	**6.7**	5.1	2.1	3.8	3.0
Bike	7.7	5.3	8.2	10.3	12.3	3.0	7.7
Urban Bus	28.5	12.8	27.4	40.1	43.4	18.3	**41.1**
Metropolitan Bus	14.6	8.9	6.0	18.0	18.0	14.7	**32.3**
Car	33.2	**58.6**	38.9	12.9	12.9	49.7	3.8
Motorcycle	1.8	1.9	**3.6**	0.9	2.1	1.0	0.8
Tram	1.1	0.4	**2.4**	0.6	1.0	0.5	**2.5**
Various modes	8.0	9.1	5.5	10.5	6.9	8.1	7.1

Note: Column headings show the corresponding sample (Complete sample and clusters C1 to C6). SD: Standard deviation.

TABLE 5.- SEM measurement model of service quality with complete sample & clusters

SRW and construct average performance	Complete	C1	C2	C3	C4	C5	C6
SQ1. Tangible Service Equipment <-- SQ	0.85 (7.97)	0.83 (7.83)	0.87 (8.29)	0.86 (8.10)	0.89 (7.69)	0.83 (7.83)	0.85 (7.83)
A1. Cleanliness of the stations	0.79	0.81	0.82	0.77	0.76	0.78	0.79
A2. Lighting in stations	0.84	0.83	0.86	0.86	0.81	0.85	0.79
A3. Lighting on vehicles	0.83	0.82	0.87	0.86	0.82	0.82	0.78
A4. Cleanliness of the vehicle	0.77	0.75	0.82	0.82	0.72	0.75	0.75
A5. Vehicle/stations temperature & ventilation	0.58	0.55	0.56	0.54	0.56	0.63	0.6
A6. Appropriate driving	0.6	0.57	0.6	0.65	0.58	0.61	0.59
SQ2. Accessibility <-- SQ	0.85 (7.98)	0.84 (7.69)	0.86 (8.21)	0.83 (7.92)	0.88 (7.65)	0.88 (7.9)	0.85 (7.9)
A7. Ease of access for people with disabilities	0.74	0.71	0.73	0.75	0.71	0.78	0.77
A8. Easy street access to stations & platforms	0.8	0.78	0.83	0.8	0.77	0.8	0.83
A9. Operation of elevators, escalators, etc.	0.75	0.75	0.75	0.72	0.73	0.77	0.79
A10. Operation of ticket validators at the entrance/exit of stations	0.68	0.67	0.71	0.66	0.63	0.74	0.65
A11. Easy use of ticket vending machines	0.67	0.66	0.67	0.65	0.65	0.67	0.69
A12. Easy connection with other modes	0.64	0.57	0.69	0.69	0.7	0.59	0.61
SQ3. Availability of the Service <-- SQ	0.83 (7.46)	0.84 (7.39)	0.81 (8.05)	0.81 (7.34)	0.81 (7.11)	0.82 (7.23)	0.84 (7.58)
A13. Number of trains per day	0.69	0.71	0.61	0.69	0.7	0.72	0.62
A14. Waiting time on the platform	0.74	0.78	0.77	0.69	0.71	0.67	0.73
A15. Speed of the trip	0.75	0.75	0.74	0.75	0.74	0.72	0.78
A16. Operating hours of the service	0.49	0.48	0.43	0.53	0.49	0.48	0.39
A17. Regularity of the service	0.57	0.63	0.53	0.52	0.56	0.58	0.51
A18. Punctuality	0.74	0.78	0.82	0.69	0.63	0.78	0.78
A19. Proximity of stations to origin/destination	(n.s.)	(n.s.)	(n.s.)	(n.s.)	(n.s.)	(n.s.)	(n.s.)
SQ4. Customer Service <--SQ	0.75 (7.59)	0.72 (7.55)	0.79 (8.04)	0.8 (7.59)	0.81 (7.25)	0.67 (7.4)	0.67 (7.6)
A20. Effectiveness and speed of employees	0.88	0.87	0.85	0.88	0.85	0.89	0.92
A21. Courtesy of the employees	0.87	0.91	0.85	0.86	0.86	0.84	0.87
A22. Performance of the Customer Service	0.83	0.78	0.81	0.89	0.82	0.85	0.86
A23. Appearance of employees	0.81	0.85	0.83	0.82	0.81	0.77	0.75
SQ5. Safety <-- SQ	0.81	0.85	0.81	0.75	0.78	0.77	0.82
A24. Sense of security against theft and aggression in stations and on vehicles	0.74	0.71	0.74	0.74	0.73	0.78	0.69
A25. Sense of security against accidents while traveling (crash/vehicle derailment)	0.78	0.77	0.78	0.8	0.78	0.73	0.76
A26. Sense of security against slipping, falling and accidents at vehicle doors and escalators.	0.75	0.77	0.75	0.73	0.73	0.75	0.76
A27. Emergency exist & extinguishers signs	0.77	0.8	0.76	0.76	0.7	0.74	0.77
SQ6. Information <-- SQ	0.81 (7.54)	0.82 (7.39)	0.86 (7.89)	0.85 (7.55)	0.78 (7.34)	0.79 (7.48)	0.77 (7.68)
A28. Updated, precise & reliable info in stations	0.83	0.82	0.82	0.87	0.78	0.84	0.84
A29. Updated, precise & reliable info on vehicles	0.81	0.79	0.77	0.81	0.79	0.85	0.85
A30. Clear and simple notice boards with info/directions in stations	0.78	0.79	0.76	0.82	0.75	0.74	0.79
A31. Information available through other communication technologies (internet, etc.)	0.59	0.64	0.57	0.58	0.49	0.57	0.62
SQ7. Environmental Pollution <--SQ	0.52 (6.4)	0.52 (6.27)	0.48 (7.12)	0.53 (6.31)	0.45 (6.06)	0.51 (6.12)	0.45 (6.46)
A32. Noise level on the vehicle	0.88	0.89	0.9	0.86	0.88	0.85	0.9
A33. Vibration level on the vehicle	0.86	0.86	0.89	0.87	0.84	0.85	0.83
A34. Noise level in stations	0.8	0.78	0.8	0.8	0.75	0.84	0.8
SQ8. Individual Space <-- SQ	0.73 (6.28)	0.76 (6)	0.71 (6.92)	0.7 (6.5)	0.68 (5.91)	0.69 (5.98)	0.71 (6.41)
A35. Seat availability in stations & platforms	0.7	0.67	0.67	0.79	0.71	0.7	0.63
A36. Level of comfort on vehicle	0.8	0.76	0.84	0.78	0.83	0.78	0.79
SQ9. Overall SQ <-- SQ	0.74 (7.61)	0.74 (7.48)	0.77 (8.28)	0.72 (7.59)	0.68 (7.12)	0.71 (7.41)	0.68 (7.73)

Note: all SRW were significant (0.1%). n.s.: not significant. COM: Complete. C1-C6: Cluster 1-Cluster 6.

TABLE 6.- SEM measurement model of attitudes with complete sample & clusters

SRW and construct average performance	Complete	C1	C2	C3	C4	C5	C6
Customer Satisfaction (CS)	(6.76)	(6.77)	(7.35)	(6.63)	(6.30)	(6.42)	(6.96)
CS1. Overall Satisfaction with the LRT service	0.72	0.72	0.63	0.72	0.75	0.76	0.62
CS2. Traveling by LRT attracts me	0.54	0.52	0.53	0.57	0.50	0.55	0.54
CS3. I feel comfortable traveling by LRT	0.65	0.63	0.63	0.66	0.60	0.62	0.73
CS4. The LRT service meets my expectations	0.66	0.65	0.59	0.66	0.69	0.69	0.63
Perceived Costs (PC)	(6.30)	(6.46)	(5.66)	(6.25)	(6.57)	(6.50)	(6.44)
PC1. I believe that the price is high.	0.84	0.86	0.85	0.85	0.83	0.83	0.81
PC2. I believe that the ticket price exceeds the costs of the LRT (staff, electricity, etc.)	0.82	0.82	0.78	0.84	0.83	0.85	0.79
PC3. I consider the costs of traveling by LRT to be high (time, money and comfort)	0.77	0.74	0.74	0.79	0.80	0.79	0.72
PC4. Stations are far away from origin and/or destination (n.s.)	-	-	-	-	-	-	-
PC5. Excessive waiting time at platforms (n.s.)	-	-	-	-	-	-	-
Perceived Benefits (PB)	(7.37)	(7.27)	(7.93)	(7.38)	(7.00)	(7.06)	(7.51)
PB1. The service of LRT is good	0.80	0.82	0.87	0.76	0.75	0.83	0.82
PB2. I believe that the quality-price ratio is appropriate	0.58	0.50	0.47	0.66	0.69	0.59	0.52
PB3. The attention to the costumer is good	0.60	0.58	0.72	0.56	0.58	0.56	0.60
PB4. I like the LRT because of the speed of trip	0.61	0.60	0.59	0.61	0.58	0.61	0.59
PB5. The timetable of the LRT service satisfies my needs (n.s.)	-	-	-	-	-	-	-
Attractive Alternatives (AA)	(4.95)	(4.62)	(4.54)	(5.28)	(5.34)	(5.13)	(5.16)
AA1. I believe that there are good alternatives of PT to the LRT (e.g. bus, taxi)	-	-	0.52	-	-	-	-
AA2. I do not mind which transport mode to use if it meets my needs	-	-	0.58	-	-	-	-
AA3. I think other modes of transport (e.g car, bus, taxi) offer more advantages than the LRT	-	-	0.53	-	-	-	-
Behavioural Intention (BI)	(8.18)	(8.19)	(8.69)	(8.15)	(7.64)	(8.08)	(8.21)
BI1. I will travel by LRT again under the same conditions (money, time and comfort)	0.77	0.80	0.77	0.74	0.83	0.70	0.69
BI2. I usually recommend the LRT service to others	0.65	0.69	0.71	0.59	0.62	0.64	0.63
BI3. Surely. I will use the LRT service again	0.72	0.80	0.72	0.77	0.74	0.64	0.66
Involvement with Public Transit (INV)	(6.41)	(6.29)	(6.70)	(6.50)	(5.99)	(6.08)	(7.01)
INV1. I feel that taking public transit is consistent with my lifestyle	0.75	0.77	0.78	0.67	0.74	0.78	0.69
INV2. I feel that by taking PT I help to protect the environment	0.63	0.61	0.60	0.63	0.66	0.65	0.63
INV3. I like others to know the fact that I take public transit	0.67	0.65	0.72	0.70	0.56	0.68	0.70
INV4. I like people who take public transit	0.75	0.76	0.73	0.76	0.79	0.74	0.71
INV5. Independently of trip purpose, I always prefer to travel by PT	0.63	0.56	0.63	0.69	0.55	0.67	0.68
INV6. I believe that using PT affects people´s opinion about me (n.s.)	-	-	-	-	-	-	-

Note: all SRW were significant (0.1%). n.s.: not significant. COM: Complete. C1-C6: Cluster 1-Cluster 6.

TABLE 7.- SEM structural model with complete sample and six clusters.

Model (SRW)			Complete	C1	C2	C3	C4	C5	C6
Structural Relationship									
CS	<-	PB	0.732	0.669	0.478	0.775	0.888	0.813	0.576
PB	<-	PC	-0.421	-0.329	-0.356	-0.480	-0.573	-0.380	-0.300
PB	<-	INV	0.352	0.277	0.216	0.390	0.298	0.490	0.391
CS	<-	INV	0.054 (0.004)	0.041 (0.244)	0.151	0.045 (0.343)	-0.050 (0.277)	0.026 (0.652)	0.184 (0.003)
CS	<-	SQ	0.386	0.493	0.540	0.317	0.22	0.277	0.371
BI	<-	CS	0.504	0.485	0.580	0.336	0.603	0.401	0.587
BI	<-	SQ	0.266	0.277	0.139 (0.011)	0.432	0.147 (0.002)	0.422	0.199 (0.002)
BI	<-	AA	-		-0.209				
Goodness-of-fit									
Sample Size			3198	843	584	535	477	394	365
Chi-squared			16,685	5,789	4,549	4,456	4,122	4,100	3,687
Degrees of freedom			1415	1415	1579	1415	1415	1415	1415
GFI			0.82	0.79	0.77	0.76	0.75	0.72	0.72
CFI			0.85	0.84	0.84	0.83	0.81	0.79	0.80
RMSEA			0.06	0.06	0.06	0.06	0.06	0.07	0.07

Note: Column headings indicate the sample used to calibrate the corresponding model (Complete sample, and clusters C1 to C6). All SRW were significant at a 0.1% level with the exception of those SRW whose p-value is indicated under parenthesis.