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Navigating Passenger Satisfaction: A Structural Equation Modeling–Artificial Neural Network Approach to Intercity Bus Services

Shaghayegh Rahnama [1,*], Adriana Cortez [2] and Andres Monzon [3]

[1] Escuela de Ingeniería y Arquitectura, Universidad de Zaragoza, 50018 Zaragoza, Spain
[2] Higher Polytechnic School, Universidad Francisco de Vitoria, 28223 Pozuelo de Alarcón, Madrid, Spain; adriana.cortez@ufv.es
[3] Transport Research Centre-TRANSyT, Universidad Politécnica de Madrid, 28040 Madrid, Spain; andres.monzon@upm.es
* Correspondence: 803982@unizar.es or sh.rahnama@upm.es

Abstract: The phenomenon of passenger satisfaction is an important issue for public transport services and transport companies. Clarifying the relationship between influencing attributes and passenger satisfaction significantly improves service satisfaction. This study examines passenger satisfaction with intercity buses and, in particular, the role of digital information channels (websites and mobile apps) in promoting sustainable travel choices on the Madrid–Bilbao route. This study analyzed data from 459 passengers to identify the key factors influencing the bus choice for intercity bus travel. Punctuality, safety, and ticket price are the most important determinants. We use a combined structural equation modeling (SEM) and artificial neural network (ANN) approach to capture the intricate relationships between service attributes and information channels. The results show that information channels, travel experience, and ticket prices significantly impact passenger satisfaction, which bus operators should improve. Also, inserting the SEM result as input for the ANN showed that ticket price is the most significant predictor of satisfaction, followed by information channels (84%) and travel experience (65%). This approach provides valuable insights for improving the passenger experience. This study emphasizes integrating digital transformation strategies into public transport systems to promote sustainable mobility goals.

Keywords: intercity bus services; passenger satisfaction; SEM-ANN

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1. Introduction

In the quest for sustainable transportation solutions, intercity bus transportation emerges as an alternative for bridging the gap between urban and rural areas, particularly in regions underserved by rail networks. This mode of transport is not only recognized for its environmental efficiency and contribution to reducing carbon emissions but also for its unique ability to provide vital connectivity to areas beyond the reach of conventional rail services. Intercity buses thus play a key role in enhancing access and mobility across diverse geographic regions, offering an economical and environmentally friendly alternative for travelers [1,2]. Their importance is highlighted in the context of sustainable transport objectives, as they extend the benefits of public transport to communities that might otherwise rely on personal vehicles due to the absence of rail options. Travel comfort is not one size fits all. Road transport dominates and offers flexibility, but traffic and distance can hinder it. Intercity buses, on the other hand, shine when traveling from city to city and in the countryside, often proving to be more sustainable and comfortable [1,2].

The attractiveness of intercity bus services as a sustainable choice is closely tied to their ability to meet and exceed passenger expectations, where factors such as punctuality, safety, and overall service quality are paramount. These elements are critical in influencing passenger satisfaction and, by extension, the propensity to choose buses over more carbon-intensive modes of transport [3,4]. Additionally, the evolution of digital information channels has significantly shaped the passenger travel experience. Modern digital platforms, including websites and mobile apps, enhance service perception through real-time information, ticketing convenience, and improved communication, further encouraging the use of intercity bus services [5,6].

Additionally, service quality (SQ) is based on how customers perceive various characteristics that define service [7]. For this, ensuring a high quality of service is critical, as it encourages more users to use the system. As mentioned, customer satisfaction and perceived service quality are closely related. According to [8,9], SQ is based on how customers perceive their trips. In other words, to increase the quality of a service, it must be tailored to customers' needs, considering different service attributes, such as the frequency, comfort, and safety, among others.

Different methodologies have been used to assess the importance of these attributes on users' overall satisfaction, such as linear regression, order logit, and probit regression. Among them, structural equation modeling (SEM) is a widely applied methodology in studies of different domains, including transport. This is because some service attributes are an abstract, poorly defined, and complicated concept that depends on several known and unknown variables [10]. Additionally, among the existing methodologies used to determine what factors contribute to passenger satisfaction, neural networks are more accurate predictors than conventional regression techniques due to their ability to grasp complex, nonlinear relationships and interactions among a wide array of factors influencing satisfactions. Despite the acknowledged significance of these factors, there remains a notable research gap regarding intercity bus services, especially in understanding how digital information channels and service quality attributes collectively impact passenger satisfaction. This study seeks to address this gap by examining the interplay between service attributes and information channels and their collective influence on passenger satisfaction within the context of the Madrid–Bilbao intercity bus route in Spain.

This study leverages a methodological approach: structural equation modeling (SEM) combined with artificial neural networks (ANNs). This SEM-ANN approach allows us to capture the complex, nonlinear relationships between service attributes, information channels, and passenger satisfaction. Traditional techniques might miss these intricate interactions. By employing the SEM-ANN, we gain a deeper understanding of the factors influencing passenger satisfaction on intercity bus routes, offering valuable insights for bus operators to enhance the passenger experience. Despite SEM's extensive applications across various fields, its integration with ANNs in public transportation research, particularly in assessing intercity bus services, represents a novel contribution. For this end, a two-step approach was used. First, SEM was used to determine which attributes (information channel and service) statistically significantly influence passengers' overall satisfaction with long-distance bus services; second, ANN models were used to rank the relative influence of the significant predictors obtained from the SEM.

This paper is divided into seven sections. Following the introduction, Section 2 offers a brief literature review of the prior research that explores customer satisfaction with public transportation, encompassing the various approaches employed. Section 3 presents the case study of our model. Section 4 presents the methodology of the proposed model. In Section 5, we present the results of the data analysis. Next, Section 6 provides a concise discussion of the research findings. Finally, Section 7 offers the overall conclusions of this work.

2. Literature Review

The study of passenger satisfaction in the public transport sector has evolved considerably, reflecting changing social needs, technological progress, and transport policy. This literature review summarizes the key findings of the previous research, focusing on service quality, passenger satisfaction, and the new role of information channels. It also highlights the novel application of the SEM and ANN methods in this area, forming this study's basis.

2.1. Passenger Satisfaction

Many researchers have focused on passenger satisfaction with public transport since the 1970s, and the development of models and questionnaires is noteworthy [11]. User satisfaction surveys evaluate the service quality offered by a public or private company by considering the customer's point of view [12]. Previous studies on public transport satisfaction include different service attributes that could be grouped depending on whether they relate to the travel experience, ticketing issues, or information channels.

Most of the attributes affecting the total satisfaction of passengers are related to their travel experience. In this regard, several studies have focused on assessing these attributes for intercity buses. Meng, Rau, and Mahardhika [13] pointed out that differences in public transportation appreciation can be linked to observable and measurable characteristics, like waiting time. Eboli and Mazzulla's research highlighted the importance of schedules, shelters, frequency of service, and punctuality in enhancing passenger satisfaction [14]. Roza et al.'s study [15] revealed that travel time, accessibility, departure frequency, and availability are key factors influencing intercity bus users' preferences. Wu et al. quantified passengers' overall satisfaction with regular bus service attributes. This analysis involved 609 passengers surveyed in Nanjing, China. Their results showed that customer satisfaction was influenced by punctuality, short waiting times, seat availability, a clean onboard environment, a pleasant station environment, convenient transfers, and air conditioning [16]. Additionally, Ganji et al.'s [17] review showed that the method of ticket reservation (cash, online, or by phone) is one of the most important attributes influencing bus passenger satisfaction.

Eboli and Mazzulla proposed a methodology for measuring transit service quality using passenger perceptions and transit agency performance measures. This approach provides a reliable tool for evaluating transit service performance. It considers customer perceptions and objective measurements provided by the transit agency. The methodology was applied to a suburban bus line case study, calculating subjective and objective indicators [14].

Rodriguez-Valencia et al. [18] analyzed user satisfaction in three public transportation bus subsystems in Bogotá, Colombia. The study used SEM-MIMIC models to identify three latent variables: condition, service, and safety/security. The findings revealed that satisfaction is influenced by a person's perception of the subsystem's condition and service, with safety and service mediating satisfaction. The research gives decision-makers a better understanding of how infrastructure, vehicles, operational attributes, and regulation processes affect satisfaction and improve public transport service. Amoah, Van Eyk et al. [19] looked into what makes South Africans who travel on long-distance coach buses happy. There are worries regarding delays, safety, and dependability, even though these buses are crucial to the economy and many people's lives. The study discovered that efficiency (arriving and departing on time) and peace of mind (feeling safe and secure) are the two most crucial elements for passenger happiness. They advised bus firms to concentrate on these areas to increase client satisfaction. The advent of digital technology has transformed the way passengers interact with public transportation services. Ghosh et al. [20] worked on improving public transportation systems' efficiency and safety by providing an overview of existing intelligent systems. It suggests a system that collects, processes, and provides necessary information about bus arrival/departure times, actual location, seat availability, accident/breakdown detection, and alerting systems. These data can be communicated via a wireless system using the GSM model, satisfying users and improving public transportation usage.

2.2. Digital Information Channels

Today's developments have prompted researchers and practitioners to reconsider service quality in the context of information technology. In recent years, web-based or mobile apps have become very popular in almost all activities [21]. Concerning bus services, IT communication channels allow customers to communicate bidirectionally with the company [22]. Turnip et al. [21] developed a mobile app that allows customers to purchase tickets and reduces waiting times.

Furthermore, Monzon et al. [23] observed that providing real-time information helps improve public transport operators' image among passengers. Romero et al. [24] studied the usage of real-time information from mobile applications by bus travelers. The findings show that frequent travelers use apps with more completed and updated information, while occasional ones utilize more general-purpose apps, like Google Maps. M. A. Javid et al. [25] established that accessibility, scheduling, and service attraction attributes significantly determine travelers' attitudes toward app-based public transport services. In another study, Romero et al. [26] worked on a transit app developed in the Madrid Region to improve the information on metropolitan buses. According to this study, providing two levels of information may be beneficial. The first level provides general information that allows passengers to choose transport modes and routes. The next level allows regular users to receive detailed information about specific routes and lines. The two levels of information improve the performance and impacts of bidirectional communication between transit operators and passengers.

2.3. Using SEM to Assess Passenger Satisfaction with Intercity Buses

Identifying factors influencing overall passenger satisfaction can help bus operators better understand service quality in different areas. Some research has focused on evaluating the quality of intercity bus services, identifying common characteristics that should be considered when analyzing bus services [1,27,28]. These findings highlight where a company should concentrate its efforts to enhance service quality and ensure user satisfaction.

Since the 1970s, SEM has been employed in different fields, including social sciences, psychology, marketing, management, economic research, and other natural sciences, to measure the link between explicit and latent variables [29,30]. SEM combines factor analysis and simultaneous equation modeling and can handle multiple exogenous and endogenous variables and latent variables specified as linear combinations (weighted averages). SEM has been utilized to simulate other areas of transportation beyond customer satisfaction with public transit, such as trip demand, organizational behavior, and driver behavior [31]. Specifically, SEM has been developed to describe passenger satisfaction with public transport services [32,33].

Results from SEM can guide service providers in prioritizing service characteristics to ensure that SQ meets or exceeds passenger expectations [34]. For instance, Wen, Lan, and Cheng [27] studied intercity bus passengers' loyalty, initially conducting an exploratory factor analysis (EFA) that identified service quality could be explained by 1—onboard amenities, 2—crews' attitude, 3—station performance, and 4—operational performance. Then, using the results from the EFA, the authors applied SEM, which showed that satisfaction has the most significant influence on passenger loyalty. Additionally, the authors observed that service value, switching costs, and trust have direct and positive effects on loyalty, whereas the attractiveness of competitors has a negative one. In another study, Yan et al. [35] used SEM to explore the relationship between socioeconomic and travel characteristics and the degree of influence on the willingness to travel by bus, finding that an individual's economic status plays a crucial role in choosing a preferred mode of transportation. For example, individuals are more likely to drive if they can park their cars easily, quickly, and affordably. Conversely, people are more likely to choose public transportation if they can minimize their waiting and transfer times and the system operates faster. Transit service quality is a complex concept influenced by various aspects, like frequency, punctuality, comfort, cleanliness, and information. Structural equation models help explore relationships between these aspects and service quality. However, the paper investigates using formative variables to model the relationship among service quality characteristics. The results show that the reflective model is more suitable for describing passenger satisfaction with transit service quality. However, some service aspects could benefit from a formative approach for better investigation [36].

The methodology section outlined the hypotheses for this study, which were based on previous research exploring SEM from the satisfaction perspective.

2.4. Using ANN to Assess Passenger Satisfaction with Transport Services

Artificial neural networks (ANNs) are information-processing systems inspired by the functioning of the human brain. They represent a fundamental aspect of artificial intelligence (AI), capable of assessing or approximatively predicting outcomes based on numerous input factors with indeterminate outputs. ANNs excel at handling small datasets through their conventional learning method, which is characterized by fewer convolutions and simplification abilities. Furthermore, ANNs can be considered an interactive modeling tool because they can interact with nonlinear entities and process algorithms without problems. Within an ANN, neurons are represented by integer values instead of binary variables, ensuring comprehensive dataset representation.

In the transportation field, Garrido et al. [37] employed ANNs to analyze the service quality in public transportation systems. Utilizing data from a 2007 customer satisfaction survey, their research uncovered significant differences in the perceived importance of attributes, such as frequency, speed, information, and proximity. These insights highlight the importance of understanding and addressing service quality in the transportation sector. More recently, Ibrahim et al. [38] applied exploratory factor analysis, correlation tests, and ANNs to identify service variables affecting user satisfaction, revealing signs, amenities, and information supply as the primary factors. Similarly, Saiyad et al. [39] used ANNs to examine how people choose their feeder modes of transportation when using the Delhi metro. The results imply that ANNs are particularly effective in learning and identifying relationships between parameters for optimal outcome prediction.

2.5. SEM-ANN

As previously mentioned, SEM is a widely used and effective method for identifying predictors significantly affecting dependent variables [40]. However, as with other traditional statistical methods, such as multiple regression analysis, it can only detect linear associations and is, thus, typically insufficient to capture the complexity of the human decision-making process. This limitation has led researchers to seek more sophisticated analytical techniques capable of elucidating the nonlinear dynamics inherent in such processes.

Researchers have relied on structural equation modeling (SEM) to validate hypothesized relationships between variables [41]. However, in recent years, the combination of SEM with the capabilities of artificial neural networks (ANNs) has increased. This integrated approach enables a deeper understanding of complex phenomena.

The earliest documented application of this hybrid method dates back to the work of [42]. However, earlier studies laid the foundation [43]. This combined approach, an ordered multi-method research design, is increasingly favored to obtain a more comprehensive picture of the research subject [40].

This is how it works: SEM is first used to rigorously test the research model and the associated hypotheses. The findings from this analysis then serve as valuable input for the ANN method [44,45]. Essentially, the factors identified by SEM are used to train the ANN, leading to the generation of estimators.

While the inner workings of a neural network may be complex [41], the real goal is to utilize its capabilities to improve the model's predictive power by building on the knowledge gained from SEM [46]. ANNs excel at tackling complex problems and often achieve higher accuracy in prediction tasks than other approaches [47]. Studies have shown that ANNs can outperform SEM regarding accurate predictions [48].

ANNs are not designed for statistical inference like SEM, which relies on detailed significance tests or rigorous data transformations. Instead, they aim to attenuate measurement error and noise in data. ANNs handle causal relationships differently, following a unidirectional flow from inputs to hidden layers and outputs, unlike SEM, which allows for relationships between hidden variables [43].

The advent of the two-step ANN-SEM technique marks a substantial improvement over conventional SEM approaches by enabling the measurement of nonlinear relationships through the use of varied activity functions and layers of hidden nodes [49], offering a nuanced understanding that linear models cannot. Furthermore, this technique facilitates the assessment of structural equation estimations even under the partial fulfilment of model assumptions, as evidenced by Chan and Chong [44] in their innovative application of ANNs to address these limitations.

Zhou et al. [50] furthered this discourse through a two-stage SEM and ANN integration aimed at evaluating strategic urban planning visions. Their method was applied to the Lantau Tomorrow Vision in Hong Kong, a large, reclaimed island. The results showed that increasing transport infrastructure accessibility should help achieve the job/population goal. Overall, as an adaptation of reference class forecasting, the SEM-ANN method is particularly interesting in front-end large-scale outline urban planning vision appraisals. Another study applied the American Customer Satisfaction Index model to investigate factors affecting passengers' satisfaction with the monorail service in Kuala Lumpur, Malaysia, employing a hybrid SEM and ANN method on data collected from 417 passengers. These findings indicated that the proposed model explains 70.4% and 59.5% of passenger satisfaction and reuse intention, respectively. Both perceived quality and perceived value were found to significantly influence satisfaction, with the ANN identifying perceived quality as the most crucial predictor of satisfaction [51].

The study from Pholsook et al. [52] proposed a hybrid three-stage approach that combines structural equation modeling, Bayesian networks (BNs), and artificial neural networks to improve passenger satisfaction. The SEM was used to test hypotheses and identify significant airport service quality (ASQ) dimensions influencing satisfaction. The BN was used to classify these dimensions into three categories based on the likelihood of occurrence in each state. The ANN was used to identify the most critical service dimension to improve satisfaction. The results provided reliable ASQ dimensions corresponding to international benchmarks and standards. The study also discussed priority factors for recovering passenger satisfaction, increasing trustworthiness, and maintaining airport service efficiency during the COVID-19 outbreak and long-term service.

The existing literature certainly provides a solid foundation for understanding passenger satisfaction. However, there is still a critical gap in examining how traditional service quality factors interact with modern information channels to shape the overall passenger experience. This study aims to address this gap by examining a representative Spanish intercity bus service. In particular, it examines how the service attributes conveyed through information channels (e.g., mobile apps or websites) influence passenger satisfaction. For this, the integration of SEM with an ANN hybrid approach combines SEM's capability for hypothesis testing and theoretical framework validation with the ANN's strength in identifying nonlinear patterns and complex relationships. As a result, the SEM-ANN model enhances the accuracy and depth of the data analysis, allowing for a more nuanced understanding of passenger satisfaction.

3. Methodology

3.1. Proposed Framework

The proposed framework for predicting passenger satisfaction includes four steps:

The first step involved conducting an exploratory factor analysis (EFA) using SPSSv24 software to identify the underlying factors influencing passenger satisfaction. EFA was chosen for its ability to reduce a large set of variables into fewer interpretable factors. The variables for the EFA were selected based on a thorough review of the literature and their relevance to this study's context.

Following the EFA, structural equation modeling was applied to model the relationship between the identified factors and overall satisfaction. SEM was selected for its robustness in handling complex, multidimensional constructs and the ability to assess direct and indirect effects. The variables introduced into the SEM were those identified as significant through the EFA, ensuring a focused examination of the most impactful factors on passenger satisfaction. In the third step, an ANN analysis used the determinants from the SEM analysis as the input variables. It predicts customer satisfaction using weights based on passenger questionnaire responses. Finally, the fourth step updated the weight from the ANN, improving satisfaction prediction accuracy with more passenger data and combining the SEM and ANN models for data mining. Figure 1 presents the methodological outline of this research work.

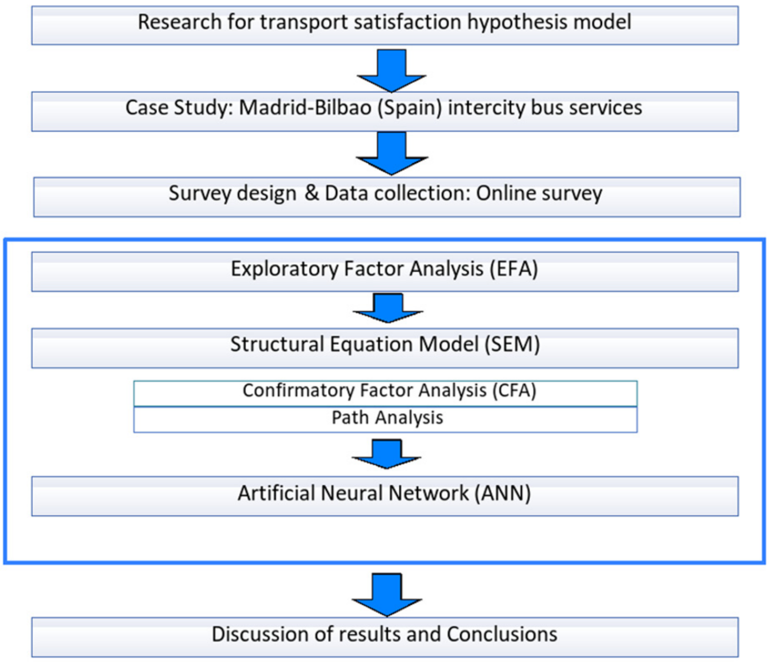

Figure 1. Overview of the research framework.

In summary:

- Conduct the EFA and passenger satisfaction surveys as planned.
- Build an SEM model using the survey data to understand the relationships between the variables and identify significant factors influencing customer satisfaction. The SEM provides insights into the "why" behind customer satisfaction.
- To predict customer satisfaction, build a separate ANN model using the same survey data (independent variables—X and satisfaction—Y).
- This leverages the identified significant variables (from SEM) for prediction.
- Train and update the ANN model with new passenger data to improve its prediction accuracy. The ANN focuses on the "how" to predict customer satisfaction with improved accuracy over time.

3.2. Survey Design

The survey aimed to assess intercity bus users' satisfaction with different attributes of the intercity bus service, with a special focus on information channels. The survey topics were defined based on the literature review (Section 2). The questionnaire was developed in Spanish, the local language, and structured into the following four parts (see Appendix A):

Part A—User profile. The first part included socioeconomic questions: labor situation, level of studies, age, and gender. Then, a group of questions on the importance of six factors for using the bus in intercity travel was selected from the literature review, like [53,54]. The questions asked for different types of responses: categorical variables, comment box, and multiple choice.

Part B—Travel characteristics. In this section, six questions were asked, including the mode used to get to/leave the station, the trip's origin, frequency, and trip purpose. As in Part A, different question typologies were applied.

Part C—Service-related attributes. Satisfaction with different attributes. In this section, the user rated the service-related attributes on a Likert scale from 1 to 5 (1 = "totally dissatisfied", and 5 = "totally satisfied").

Part D—Information channels. Two types of information channels were examined: web and mobile app. Bus passengers rated the reliability and ease of use of eight mobile app and web features on a Likert scale, ranging from 1 to 5, to determine their agreement with different statements on the features (1 = "totally disagree", and 5 = "totally agree").

3.3. Data Collection and Sample

The survey used a hybrid methodology developed by [55]. This strategy combines cutting-edge technology platforms with conventional survey techniques. It combines face-to-face contact for motivation and project information, delivering a card with individual access to a web survey. The SurveyMonkey platform was selected because of its easy-to-use interface and practical data management features. Furthermore, the distribution of cards containing project data and login credentials guaranteed consistent web survey access, improving response rates. A prize draw was offered to all respondents who completed the survey to improve the response rate [56]. Survey cards were distributed to passengers at boarding places for the selected intercity bus services. For this study, they were distributed at the Avenida America interchange in Madrid, the origin of the Madrid–Bilbao bus services. The surveys were randomly distributed without regard to the type of passengers and their socioeconomic and ethnic status but fulfilling gender and age quotas to be representative. The survey was performed in two different seven-day stages in 2021: (1) in the middle of summer vacation (August) and (2) in October on weekdays to capture occasional and frequent users, respectively. The surveys were distributed to travelers of 25 expeditions per stage. A total of 2000 survey cards were distributed, of which 459 valid responses were collected. This robust response rate underscores the reliability and validity of our dataset.

3.4. Data Analysis

ANOVA can detect significant differences across variables but cannot explain these discrepancies. Structural equation modeling (SEM) adopts a more comprehensive methodology. It is useful for comprehending the causal relationships between various variables, including those that are difficult to measure directly [57]. Because SEM takes into account both observable and latent characteristics, it has advantages over standard statistical approaches.

SEM was utilized in this study to investigate how user profiles—such as age and experience—affect preferences for information channels and, in turn, customer satisfaction with service features. It models a causal relationship that considers both observable and latent factors. The data were analyzed using various statistical methods, including factor analysis, route analysis, and regression models. The two components of SEM are (1) a structural model that evaluates the strength of causal linkages between latent variables and (2) a measurement model that depicts the interaction between latent and observable variables.

For SEM estimation, we used the maximum likelihood (ML) technique with AMOS26 software, which we chose based on how well it fits our study's goals and the data's features. Other methods, such as asymptotically distribution-free weighted least squares (ADF-WLS) and generalized least squares (GLS), can also be used to estimate the SEM's parameters [58,59]. According to Golob [59], the selection of the most suitable estimating method depends on several assumptions, including the sample size, scale of the variables, and probability distribution.

Structural equation modeling (SEM) offers significant advantages, including factor loadings, composite reliability, the average variance extracted, and several goodness-of-fit indices. Factor loadings show how well each question represents its underlying concept;

high values indicate good representation. Indices such as the Tucker–Lewis Index (TLI) and the Normed Fit Index (NFI) should have values above 0.9 to indicate a good fit. Similarly, RMSEA (root mean squared error of approximation) indicates a good fit if values are less than 0.08. Using these indications, researchers can find problematic issues that need improvement and confirm the accuracy of their results using SEM. The research design is supported by this iterative approach, which also provides more reliable results.

Then, the hybrid modeling technique, combining ANNs and SEM, was applied to assess customer satisfaction with intercity bus services. SEM provides insightful information about the causal connections between different elements affecting passenger satisfaction. ANNs then use these insights to create more accurate predictive models. ANNs are powerful tools for predicting passenger satisfaction in the transportation industry. They analyze real-world data, including factors like seat comfort and cleanliness, to uncover hidden relationships. ANNs can predict satisfaction for new scenarios, allowing operators to allocate resources effectively. They can highlight factors influencing satisfaction, allowing them to prioritize improvements like comfortable trips or stricter on-time arrival schedules. This two-step process enables a more accurate evaluation of the relative importance of the significant factors influencing passenger satisfaction and offers a deeper knowledge of those factors. Using this methodology, bus operators may improve passenger experiences by using important, data-driven insights to inform service performance and planning.

3.5. Developing Hypotheses on the Determinants of Passenger Satisfaction

Data analysis using statistical techniques like factor analysis, path analysis, and regression models offers benefits, such as understanding complex information, identifying underlying factors, and predicting hypotheses. These techniques validate conclusions, manage complexity, support iterative development, and have real-world applications. Combining methods like artificial neural networks, structural equation modeling, and exploratory factor analysis allows for a detailed analysis of passenger satisfaction factors.

As with other researchers in this area, we created groups of attributes in the survey to make it easy to understand. For example, ticketing includes ticket prices, a variety of fare types, and ease of purchasing tickets. Travel experience is another category that shows attributes like information inside the bus, accessibility, heating and air conditioning, correct and adequate information, appearance and image of the driver, etc. Table 6 shows these categories of attributes.

Preciado-Ortiz [60] studied the impact of a mobile transport application on the satisfaction of university students. Model validation was performed using partial least square structural equation modeling (PLS-SEM). They observed that design, information, and system quality are predictors of satisfaction. The study of Watkins et al. [61] showed that real-time mobile information from websites, cell phones, text messages, and smartphones did not significantly affect passengers' perceptions of waiting time. Choi et al. [62] studied people's willingness to keep using mobile apps for travel and the factors that affect that decision. Using the expectation confirmation model framework and interviews, the authors proposed a model that explains the connection between functional value, hedonic value, satisfaction, and trust. Additionally, it covers how familiarity, trip objective, travel app type, and technical proficiency affect usage frequency.

Therefore, the below hypotheses are proposed:

H1. *Information channels are positively related to overall satisfaction.*

H2. *Information channels are positively related to the ticket price.*

H3. *Information channels are positively related to the travel experience.*

Quality of service is closely linked to passenger satisfaction, which is a significant determinant of transport demand [63]. Factors affecting the performance of bus service quality have recently received significant attention. While the performance evaluation of bus transport has been fundamental to operators, there is an increasing emphasis on a better understanding of service quality attributes concerning the customers' needs [64]. This is because a strong connection has been established between service attribute quality and customer satisfaction. Service providers are willing to better understand the factors affecting customer satisfaction to foster sustainable mobility [65]. In other research, J. de Oña et al. [66] focused on passengers' behavioral intentions to use transit services. They identified one latent variable called "perceived benefit", which is formed by different travel experiences and that was shown to have a high influence on behavioral intentions. Moreover, this latent concept is influenced by attitudes toward transit and perceived costs. Therefore, transit management can achieve the desired user behavioral intentions by lowering perceived costs and promoting positive attitudes toward transit (e.g., loyalty and referral).

Based on the previous statements, the below hypotheses are proposed for this research work:

H4. *Travel experience is positively related to overall bus satisfaction.*

H5. *Travel experience is positively related to the ticket price.*

Islam et al. [67] studied factors measuring customer satisfaction. They observed that the ticket price, the drivers' way of driving, services inside and outside the bus, the layout of the stops, and the safety of the route have the greatest response rate (95.8%) among the different factors considered to assess customer satisfaction. Access to stops and ticket prices are second in terms of customer satisfaction (90.6%). Therefore, the below hypothesis is proposed:

H6. *Ticket price is positively related to total bus satisfaction.*

The structural model shown in Figure 2 is proposed and tested following these hypotheses using the SEM-ANN technique.

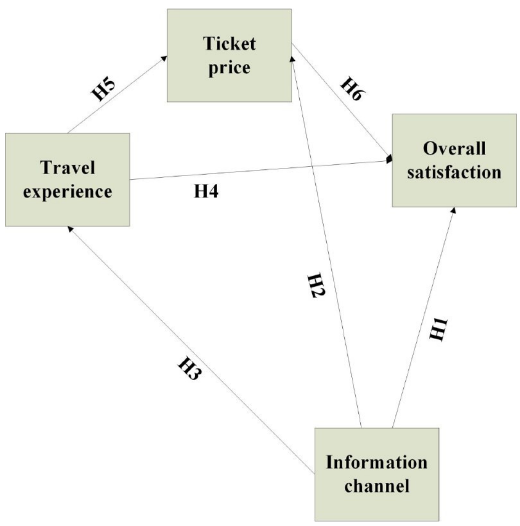

Figure 2. Structure of the proposed SEM.

4. Case Study

This section delves into a case study: the intercity bus services between Madrid, the capital city of Spain, and Bilbao, its fifth-largest metropolitan area. This route, with numerous daily trips from Madrid's Avenida America interchange station to Bilbao, is a prime example of intercity bus services. Alsa, one of the leading companies in this sector, operates on this route. In 2024, the ticket price for a one-way bus trip between these two cities is 35–65 EUR, and the journey time is around 4:30. The choice of this route for our analysis is significant due to the following:

Representative intercity route: The 398 km distance between Madrid and Bilbao falls within the typical range for Spanish intercity bus routes. By studying the ridership patterns and service options on this route, we can gain valuable insights that are likely to apply to a significant portion of the intercity bus network in Spain.

A microcosm of intercity travel: Madrid and Bilbao, as major population centers, generate a high potential ridership for intercity travel. Analyzing the ridership on this route provides insights into the factors that influence passenger choices and preferences when compared to alternative travel options. This understanding could be used to extrapolate findings to other intercity routes.

Varied topography: The route passes through two big mountain ranges: Sierra Central and Cantabrian Mountains. The regions crossed present unique challenges and opportunities for developing long-distance bus infrastructure.

(I) Mountainous landscape: This topography may require more maintenance of roads for safe and efficient bus transportation. Mountainous landscapes with steep inclines and declines, for example, significantly impact travel times and make it difficult to predict journey times. Winding roads in mountain ranges also increase travel time and require slower speeds than flat landscapes.
(II) Weather: Stormy weather, such as snow and fog, can affect road accessibility. Addressing these issues requires strategic investment in infrastructure, including improved signage, weather monitoring systems, and slope stabilization works. This type of weather can also be unpredictable and cause delays and schedule disruptions.
(III) Route planning: Mountain ranges can affect route planning by influencing peak changes, road curves, and potential weather-related problems.

Bus terminal infrastructure: The availability and accessibility of bus terminals play a significant role in passenger movement and transfers. Investing in modern terminals with waiting areas, restrooms, and ticketing facilities enhances the passenger experience.

5. Results

Our investigation shows insights into passenger satisfaction in the intercity bus service industry and provides significant information beyond the Madrid–Bilbao route. The demographic of customers using intercity bus services tends toward younger individuals, who prioritize the price and convenience of these trips above everyday commutes. A significant fraction of intercity bus passengers are middle-class people, demonstrating the sector's accessibility to a wide range of socioeconomic categories. Some results, as mentioned before, show findings through the intercity services with a standard km distance and can show a more general view of most intercity bus services and their operator to find key elements for improving passenger satisfaction.

This section presents the analysis of the results of the different research stages.

5.1. User Profile

The socioeconomic characteristics of the sample adjusted for sample weights are shown in Table 1. As we mentioned before, 459 valid responses were gathered from a total of 2000 cards that were distributed. It comprises more females (61%) than males (37%) and other (2%). Most respondents are between 36 and 60 years old (34%), and the following largest groups are 18–25 years old (32%) and 26–35 years (25%). Groups younger than 18 and older than 60 are underrepresented (3% and 6%, respectively). Users generally have a university degree (60%) or a bachelor's degree (28%), but there is also a small group that has a high school degree (6%). The main occupations of passengers are employed and students (51% and 29%, respectively). In total, 67% of the passengers have a driving license, and only 35% own a car. Moreover, 64% of the passengers have a public transport card. Most respondents have a medium income (1300–2500 EUR).

Table 1. Madrid–Bilbao socioeconomic attributes of surveyed travelers.

Attributes	Category	Total Sample %
Gender	Female	61%
	Male	37%
Age (years old)	<18	3%
	18–25	32%
	26–35	25%
	36–60	34%
	>60	6%
Level of studies	Primary	1%
	High school degree	6%
	Bachelor	28%
	University degree	60%
	Others	5%
Occupation	Student	29%
	Worker (employee/employer)	51%
	Household worker	3%
	Unemployed	8%
	Retired	5%
	Other	4%
Availability of modes of transport	Driving license	67%
	Own car	35%
	Motorcycle or moped	5%
	Own bicycle	26%
	Public Transport card	64%
	None of them	6%
Income	<1300 EUR	36%
	1300–2500 EUR	41%
	>2500 EUR	23%

5.2. Travel Characteristics

Analyzing travel characteristics such as frequency and purpose can help the operator understand passenger behavior. Table 2 shows the passengers' travel characteristics. It can be observed that the main reasons for traveling are leisure (61%) and work (15%). Only 4% of passengers travel once or twice a week, while the majority (74%) are occasional travelers. Regarding the type of ticket used, there is a similar distribution between passengers who purchased round-trip tickets (51%) and those buying one-way tickets (45%).

Table 2. Travel characteristics of Madrid–Bilbao coach services (source: survey).

Attributes	Category	Total Sample %
Frequency of trip	1 or 2 times a week	4%
	Few times a month	22%
	Occasionally	74%
Trip purpose	Work	15%
	Study	5%
	Leisure	61%
	Other	19%
Type of ticket	Single	45%
	Round trip	51%
	Frequent voucher	2%
	Other	2%

The main access mode to the Avenida America origin station in Madrid is the metro, and it is also the main dispersion mode in Bilbao to reach final destinations. It accounts for

62% and 34% of the passengers, respectively (Table 3). Walking has a relevant share with 12% and 21% in Madrid and Bilbao, respectively. Taxi and car-as-a-passenger account for 12% and 15% in Madrid and 8% and 25% in Bilbao. As expected, the number driving to both stations is rather low because of the parking difficulties; this is a clear deterrent factor in Madrid (0% or car-as-a-driver), while it is only 3% in Bilbao.

Table 3. Access and egress modes.

Mode	Access Mode Madrid (%)	Egress Mode Bilbao (%)
Metro	62%	34%
Suburban rail	5%	4%
Interurban bus	7%	7%
Urban bus	5%	7%
Taxi	12%	8%
Car as driver	0%	3%
Car as passenger	15%	25%
Motorbike	0%	0%
Bicycle	1%	0%
Walking	12%	21%

5.3. Rating User Satisfaction

All the respondents were asked to rate the importance of six attributes for using the bus (Table 4). The results show that the main attributes that encourage passengers to use buses are punctuality/reliability (4.73), followed by ticket price (4.48) and safety (4.46). On the other hand, accessibility for RMP (3.94) and connection with other modes (3.93) are considered less important.

Table 4. Importance of different attributes for using intercity buses.

Trip Attributes (Likert Scale 1–5)	Mean	Std. Dev.
Punctuality/reliability	4.73	0.6
Duration of trip	4.41	0.77
Ticket price	4.48	0.76
Connection with other modes	3.93	1.03
Safety	4.46	0.77
Accessibility for reduced mobility passenger (RMPs)	3.94	1.25

The correlation between the importance of different attributes for choosing intercity buses and passenger socioeconomic characteristics was assessed using one-way ANOVA. The results of Table 5 allow us to evaluate if there is any relationship between the importance of different factors for using the bus and socioeconomic characteristics. It is observed that the importance of punctuality/reliability is not related to passengers' socioeconomic characteristics. However, the remaining five trip attributes are related to at least one socioeconomic characteristic, gender being the most common among them.

Table 5. Relationship between passengers' profiles and reasons for using bus for intercity trips.

Trip Attributes	Passengers' Socioeconomic Characteristics	F	$p < 0.05$
Duration of trip	Occupation	10.64	0.00
	Age	9.34	0.00
	Gender	6.94	0.00
Ticket price	Occupation	6.74	0.00
	Income	10.84	0.00
Connection with other modes of transport	Age	3.56	0.02
Safety	Gender	11.49	0.00
	Age	3.96	0.01

Table 5. *Cont.*

Trip Attributes	Passengers' Socioeconomic Characteristics	F	$p < 0.05$
Accessibility for reduced mobility passenger (RMPs)	Gender	15.12	0.00
	Level of studies	16.40	0.00
	Income	5.15	0.00

5.4. Passengers' Satisfaction with Service-Related Attributes

We assessed passenger satisfaction with eighteen service attributes; their average rate is presented in Table 6. As mentioned in our hypothesis, attributes are collected in two categories for a better description. As can be seen, punctuality, "smoothness in driving", and the feeling of safety during the trip are the best-rated attributes, with an average rate of 4.3/5, followed by the driver's appearance and image (4.1/5). It shows that satisfaction with the safety attributes of the service is high in total. On the other hand, ticket prices and various fare types are the worst-rated attributes. Finally, it is essential to mention that most passengers did not rate the attributes related to the interaction with the company (notifications of incidents in the service and ease of contact with the company) and lost/found service.

Table 6. Passengers' satisfaction with different service-related attributes.

Attributes (Likert Scale 1–5)	Mean	Std. Dev.
Ticketing		
Ticket prices	3.3	1.03
Variety of fare types	3.0	1.16
Ease of purchasing tickets	3.0	1.85
Travel experience		
Information inside the bus	3.5	1.28
Accessibility	3.5	1.28
Heating and air conditioning	3.8	0.98
Correct and adequate information	3.8	1.13
Appearance and image of the driver	4.1	1.19
Smoothness in driving (curves, braking)	4.3	0.77
Sense of safety during the trip	4.3	0.83
Duration of the trip	3.7	1.06
Time of access to the bus	4.08	0.86
Punctuality of departure	4.3	0.90
Auxiliary services of the company	3.37	1.56
Notifications of incidents in the service	2.33	1.94
Lost/found service	1.1	1.79
Ease of contact with the company	2.3	1.91
Security and baggage control	3.6	1.32

The relationship between socioeconomic, travel characteristics, and passenger satisfaction with the different service-related attributes was examined. Table 7 shows that the satisfaction with 8 of the 18 service-related attributes is significantly different for passenger's age and income and the frequency and purpose of the trip.

Table 7. ANOVA test for satisfaction of service-related attributes and user profile.

Attributes	Passengers' Socioeconomic and Travel Characteristics	F	$p < 0.05$
Ease of purchasing tickets	Age	18.16	0.00
Duration of the trip	Frequency	4.17	0.04

Table 7. *Cont.*

Attributes	Passengers' Socioeconomic and Travel Characteristics	F	$p < 0.05$
Access time to the bus	Trip Purpose	7.08	0.00
Punctuality of departure	Frequency	5.02	0.02
	Trip Purpose	10.29	0.00
Auxiliary services of the company	Trip Purpose	4.67	0.03
	Income	5.66	0.00
Notifications of incidents in the service	Income	5.08	0.00
Lost/found service	Income	7.24	0.00
Security and baggage control	Trip Purpose	5.41	0.02

5.5. Evaluation of Information Channel Features According to Users

Part D of the survey was focused on assessing the perceived quality of the company's information channels (web and mobile app). In the survey, passengers had to choose the type of information channel they use most frequently for their trip from three options: website, mobile application, and others. Of all the respondents, 160 (34%) use the mobile app, and the remaining 272 (59%) use the website to plan their trips. Among mobile app users, 68% are women and 30% are men, while website users have a higher percentage of men, with 58% women and 42% men. Regarding age, people between 18 and 25 years old (39%) represent the highest percentage of mobile app users, while people between 36 and 60 years old (36%) are the highest share of web users. Considering that the frequency of travel can impact the platform chosen, the mobile app and web were analyzed separately. Among the app users, 35% are travelers who take a trip a few times a month, and 59% travel occasionally. On the other hand, 82% of web users travel occasionally.

The passengers were asked to assess to what degree they agreed with eight statements related to the functioning of the information channels (web/mobile app) they use more frequently to plan their trips. Table 8 presents the average rate of each feature. The web and mobile app data are perceived as reliable, with the highest total agreement scores (4.2 and 4.4, respectively). In the second place, users agree that the mobile app and web are "easy to use" and "always up to date", with the average rates equal to or over 4. On the other hand, interacting with the company and obtaining an immediate response to different incidents is the worst perceived feature of the mobile app and web.

Table 8. Users' value of information channel features (web and mobile app).

Features of Info Channel	Web		Mobile App	
	Mean	Std. Dev.	Mean	Std. Dev.
Easy to use	4.0	0.84	4.3	0.77
Reliable data provided by the mobile app or web	4.2	0.87	4.4	0.75
Always up to date	4.0	0.86	4.1	0.84
Obtain real-time information on bus occupancy	3.4	1.08	3.5	1.15
Access information related to tickets purchase	3.8	1.04	4.0	1.06
Immediate response to incidents	3.1	1.04	3.2	1.13
Define preferences about the cost of my trip	3.9	1.06	3.8	1.04
Define preferences about the duration of my trip	3.6	1.22	3.6	1.11

ANOVA was used to explore if there was a significant relationship between the perception of the different features of the web, mobile app, and user profile. All the characteristics considered in parts A and B of the survey were considered. Table 9 shows that trip frequency, trip purpose, and gender are the factors that have a statistically significant relationship with users' perception of the information channels' features.

Table 9. ANOVA of features in information channels and user profiles.

Features of Info Channel	Attribute		Loading Factor		$p < 0.05$	
	Web	Mobile App	Web	Mobile App	Web	Mobile App
Easy to use	Frequency	Frequency	17.42	23.52	0.00	0.00
Reliable data provided by the mobile app or web	Frequency	Gender Frequency	21.86	5.97 21.03	0.00	0.00 0.00
Always up-to-date	Frequency	-	20.79	-	0.00	-
Obtain real-time information on bus occupancy	Frequency Trip purpose	Gender	18.17 4.14	6.80	0.00 0.04	0.00
Access information related to the purchase of tickets	Frequency	-	19.08	-		-
Immediate response to incidents.	Frequency Trip purpose	Gender	21.90 4.62	9.48	0.00 0.03	0.00
Define preferences about the cost of my trip	Frequency	Frequency	21.81	13.59	0.00	0.00
Define preferences about the duration of my trip	Frequency	-	19.06	-	0.00	-

5.6. Exploratory Factor Analysis (EFA)

An exploratory factor analysis (EFA) was conducted to examine the association between items (information channel features and service attributes) and the important construct (variable). Table 10 presents the three factors identified and the loadings of all 24 items. The variance explained by the factors is 74%, which is aligned with the recommendation of Field et al. [68], which establishes that the variance explained by all components should be between 70% and 80%. Cronbach's alpha value, ranging from 0 to 1, was used to evaluate the reliability of the factors obtained. As can be seen in Table 10, the three factors identified can be considered reliable following the criteria of Uluskan [69], which indicates that Cronbach's alpha greater than 0.6 represents sufficient reliability. The factors were named depending on the items that comprise them: information channels, travel experience, and ticket price. The models developed in the subsequent sections utilized these factors.

Table 10. Exploratory factor analysis for information channel features and service-related attributes.

Factor Name Cronbach's Alpha (α)	Factor Loading
Information channels (0.84)	
Easy to use	0.72
Reliable data provided by the mobile app or web	0.71
Always up-to-date	0.69
Obtain real-time information on bus occupancy	0.66
Access information related to tickets purchase	0.62
Define preferences about the cost of my trip	0.58
Define preferences about the duration of my trip	0.56
Travel experience (0.83)	
Information inside the bus	0.64
Accessibility	0.63
Heating and air conditioning	0.61
Correct and adequate information	0.57
Ease of contact with the company	0.54
Smoothness in driving (curves, braking)	0.52
Sense of safety during the trip	0.78
Duration of the trip	0.73

Table 10. *Cont.*

Factor Name Cronbach's Alpha (α)	Factor Loading
Time of access to the bus	0.70
Punctuality of departure	0.52
Auxiliary services of the company	0.71
Ticket price (0.69)	
Ticket prices	0.74
Variety of fare types	0.73
Ease of purchasing tickets	0.73

5.7. Modeling Structural Equations to Test Hypotheses

The IBM AMOS software 27 was used to test the path model suggested (see Figure 3). The first analysis showed the following paths:

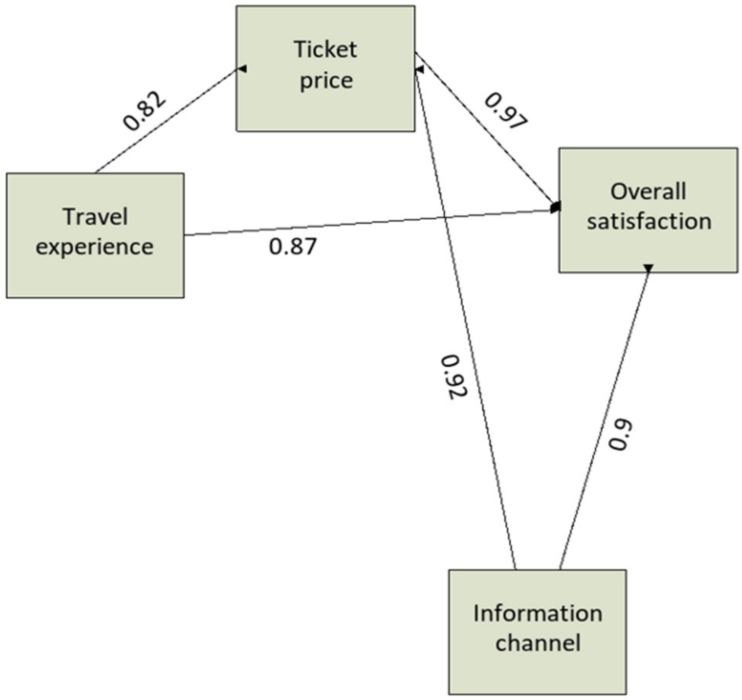

Figure 3. Path analysis model related to overall satisfaction (standardized regression weights).

Travel experience and ticket price (H5), travel experience and overall satisfaction (H4), information channels and overall satisfaction (H1), information channels and ticket price (H2), and ticket price and overall satisfaction (H6) have significant relationships.

After the path model was redrawn in AMOS, the fit indices of the model were analyzed. The results show the fit indices of the model and their recommended thresholds. Table 11 presents the estimated standardized path and coefficients of determination ($p < 0.001$). Following the work of Lopez-Carreiro et al. [70], we examined the goodness of fit of the model by using the root mean square error (RMSE), which is the difference between the actual and predicted values of the output variables and is commonly used to assess whether the neural network model is accurate [71].

Additionally, the standardized root mean square residuals (SRMRs) and the comparative fit index (CFI) were estimated. The model's overall fit was satisfactory (RMSE = 0.06; SRMR = 0.04; and CFI = 0.9).

Table 11 and Figure 3 show that the final model has three direct relations and two indirect relations with their standardized regression weights. Travel experience, information channel, and ticket price directly affect overall satisfaction with intercity bus services. In addition, information channels and travel experiences affect ticket prices.

Table 11. Results of the hypothesis testing.

Hypothesis	Path			SE	*p*-Value	Support
H4	Travel experiences	→	Overall satisfaction	0.037	0.00	Yes
H1	Information channels	→	Overall satisfaction	0.027	0.00	Yes
H6	Ticket price	→	Overall satisfaction	0.038	0.00	Yes
H2	Information channels	→	Ticket price	0.021	0.00	Yes
H5	Travel experiences	→	Ticket price	0.024	0.00	Yes

5.8. SEM-ANN

The synergistic approach provided by the combined analysis of SEM and an ANN addresses the limitations of each technique alone. Complex interactions between variables can be well modeled by SEM. However, it may require assistance in capturing the subtleties of human decision-making. The combined strategy minimizes SEM's inadequacies by including an ANN, which excels at managing complicated patterns and nonlinear interactions, incredibly when comprehending the intricate decision-making processes involved. By using the statistically significant determinants found by SEM as input variables for ANN analysis, this integration improves the prediction model's accuracy and resilience [71–74]. The predictive potential is enhanced by this integrated research, especially when forecasting overall satisfaction, depending on factors like travel experience, ticket cost, and information sources. Multilayer Perceptrons (MLPs) are an increasingly common form of an ANN helpful for collecting complex patterns and generalizing from data because of their flexibility, adaptability, and immunity to noise. Utilizing the advantages of both SEM and ANNs, the combined analysis thoroughly comprehends intricate phenomena, including consumer satisfaction in travel experiences. It provides insightful information for formulating strategies and making decisions.

Three fundamental components comprise an essential ANN: an input, hidden, and output layer (Figure 4). The MLP, a more complicated ANN, comprises several hidden layers [75]. A common ANN type utilized is the MLP. For applications involving pattern identification and classification, MLPs are especially helpful. MLPs are robust tools frequently utilized because of their adaptability and capacity to learn intricate patterns. An ANN employs MLPs as it helps to resolve nonlinear issues by approximating nonlinear functions. Additionally, MLPs can generalize new data effectively and are resilient to noise.

In MLPs, information is transferred from the input layer to the output layer. The input layer receives the raw data or input signal to the process. While the hidden layers perform computations, the output layer offers predictions or classifications [76].

The model used in this study contains a hidden layer, with the number of neurons automatically determined by the SPSS software 29. Standardization processing was performed before with the data input, followed by the definition of the training function and parameters [77]. In addition, ten-fold cross-validation was performed throughout the training to prevent overfitting the neural network [38]. Overall, 20% of the data were used for testing and the remaining 80% for training the network [78]. The sigmoid function was used for the output and hidden one.

The RMSE values were used to monitor the accuracy and performance of the neural network models for each fold. Table 12 shows these values for the training and testing datasets of the models (each with ten iterations) with an average of 0.13. The small values of the average RMSEs of the training and test datasets show that the model provides accurate predictions [40,79]. It can also be observed that the RMSE values of the test sets are smaller than the ones of the training sets. For further details on how using the training dataset as a reference improved prediction, the ANN model offers excellent data fit, good prediction accuracy, and minimal error thanks to the low mean RMSE values.

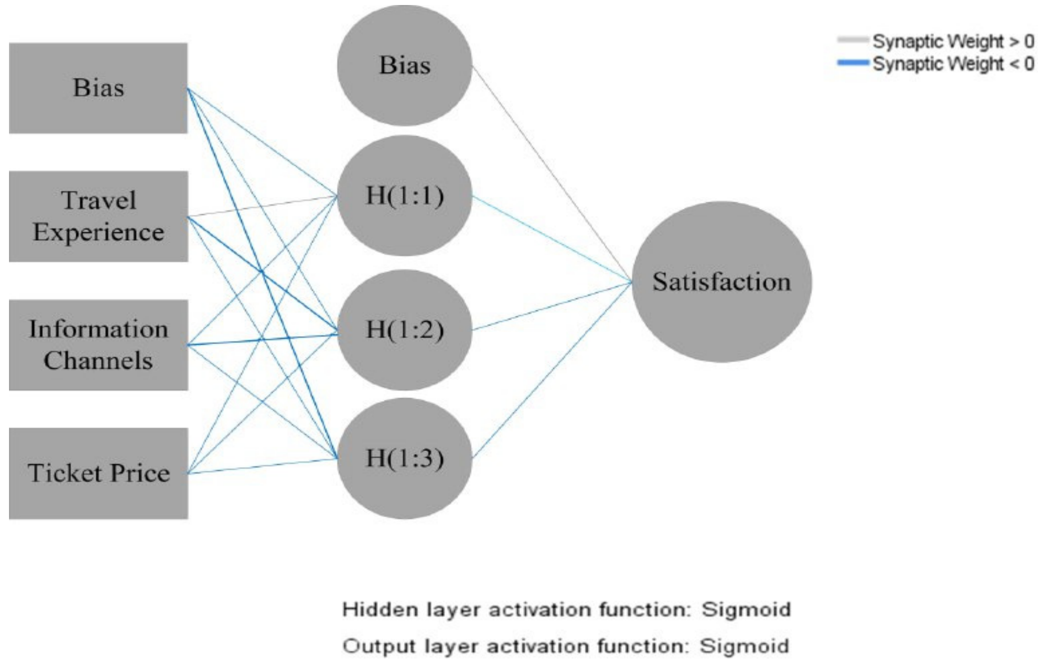

Figure 4. Proposed ANN model.

Table 12. RMSE values for the ANN model.

Network	Input: Travel Experience, Ticket Price, and Information Channels Output: Total Satisfaction			
	Training	**Sample Size**	**Testing**	**Sample Size**
1	0.13	342	0.12	91
2	0.13	350	0.12	83
3	0.12	352	0.13	81
4	0.13	342	0.13	91
5	0.13	358	0.11	75
6	0.12	346	0.13	87
7	0.13	336	0.13	97
8	0.12	354	0.13	79
9	0.12	326	0.14	107
10	0.13	350	0.12	83
Mean	0.13		0.13	
SD	0.002		0.008	

5.9. ANN Sensitivity Analysis

A sensitivity analysis was used to assess the relative importance of input variables as predictors [80]. Based on Ibrahim et al. [38], the extent to which the expected output value differs for different values of the input variables is determined by the relative importance of each input variable. We have used a sensitivity analysis (see Table 13) to determine the normalized importance of these neurons by dividing their relative value by the most significant importance and displaying it as a percentage to assess the strength of the predictive potential of each of the input neurons.

Table 13 provides the relative and normalized importance of each input variable for all the models. According to the ANN sensitivity analysis, ticket price is the most significant predictor of satisfaction, followed by information channels (84%) and travel experience (65%).

Table 13. Importance of each input variable.

Network	Information Channels	Ticket Price	Travel Experience
1	0.11	0.95	0.36
2	0.55	0.98	0.51
3	0.98	0.83	0.34
4	0.98	0.55	0.72
5	0.25	0.93	0.23
6	0.87	0.90	0.73
7	0.97	0.97	0.42
8	0.18	0.95	0.38
9	0.96	0.57	0.60
10	0.96	0.39	0.95
Normalized importance %	84%	100%	65%

6. Discussion

Passengers' demographics and travel attributes are essential to fulfill passenger requirements. Although the Madrid–Bilbao route was the focus of our investigation, the same trends can be seen in other intercity bus services. Operators can allocate resources more effectively to meet passengers' needs by comprehending user profiles and their influence on satisfaction. Investing in user-friendly digital platforms can significantly enhance the passenger experience by providing information channels. Operators can use digital interfaces for information dissemination and service value enhancement. This can be achieved by prioritizing improvements in website and application services.

The results of the SEM analysis support the validity of the questionnaire used in this study. High factor loadings (above 0.7, for example) show that the survey questions captured the intended constructs well. Good SRMR values (below 0.08) indicate that the intended concepts were effectively measured in the questions. Finally, the fit indices, including the CFI (above 0.9, for instance), confirm the consistency of the general SEM model with the data collected.

The SEM-ANN method's stability across different samples merits attention [81]. SEM can be sensitive to sample size, potentially yielding variable results with smaller datasets [82]. Additionally, the quality of the questionnaire used in SEM analysis impacts stability [83]. ANNs, known for their data-driven nature, are susceptible to variations in training data; significant differences between training and new data can lead to unstable predictions [84]. The SEM-ANN combination inherits these stability concerns, as the ANN relies on the relationships identified by SEM.

6.1. User Profiles for Intercity Bus Services

Passengers' socioeconomic and travel characteristics were analyzed to identify user profiles. As previously observed by [85,86], intercity bus users have a higher percentage of medium-income women. The most important attribute for using the bus is punctuality, which was previously observed by [87], followed by travel safety. In contrast, correspondence with other modes of transport seems to be the least important factor in choosing intercity buses. Most passengers travel only occasionally, and the main reason is leisure followed by work, as stated by [85].

When reviewing intercity bus services, factors like safety, ticket price, punctuality/reliability, and accessibility have been considered more significant than reduced mobility passengers (RMPs). This lower ranking implies that travelers value characteristics that directly impact their unique travel experiences, such as affordability and punctuality, more than accessibility and multimodal connection. It can indicate that people believe RMP accessibility is currently sufficient or that other elements that have a more significant direct impact on the general comfort and quality of bus travel are given less importance.

Comparably, the significance of connections with other modes is rated less highly, suggesting that the main components of the trip are prioritized. This could indicate that travelers think the existing state of intermodal connectivity is adequate, or it could be the result of sample bias where some passenger viewpoints are underrepresented, such as those who need accessibility features or depend on connections for longer travels. Recognizing that, even though labeled as "less important", some elements are significant for specific passenger groups or travel situations, this should not be taken lightly.

Regarding the ticket type, round-trip and one-way tickets are the most used with similar shares. The one-way ANOVA results show no statistically significant relationship between passenger's travel characteristics and the importance of the different attributes for using the bus. On the other hand, age, gender, occupation, and income are related to the importance of at least one of the attributes considered.

6.2. Satisfaction with Different Service-Related Attributes

We evaluated passengers' satisfaction with the 18 service-related attributes and analyzed whether it relates to their socioeconomic and travel characteristics. Attributes belonging to safety are the best-rated ones, together with service punctuality, which was also observed previously by [88]. On the other hand, attributes grouped as "travel experience" are identified as weaknesses due to their low ratings, particularly the lost/found, which is rated 1.1/5. In this same line, ticketing-related attributes such as the ticket price, fare variety, and purchasing options are fairly rated compared to other categories, which was also observed by [89].

The results show that passenger satisfaction with eight of the eighteen service attributes evaluated is related to their age, income, or the frequency and purpose of their trips. Satisfaction with the ease of purchasing tickets is related to the passengers' age, backed by complaints from elderly passengers who demanded a face-to-face sales service. Regarding travel characteristics, both the frequency and purpose of the trip are shown to be related to passengers' satisfaction with the duration of the trip and the punctuality of the services. As would be expected, frequent travelers are less flexible with timing issues. Finally, passengers' income is related to their satisfaction with complementary services like lost/found and notifications of incidents. It is observed that higher-income passengers are pickier with these kinds of customer services.

6.3. Evaluation of Information Channel Features

The value of the company's information channels (web and mobile app) was assessed. Passengers were asked to state to what extent they agreed with eight statements related to the functioning of the channel they use most frequently. Data reliability is identified as the best-rated feature of both the app and the web. Additionally, passengers consider both channels "easy to use" and "always up to date", which is supported by the high scores for these two features. On the opposite side, the worst-rated feature is also coincident for both channels and is related to the company's speed of response in case of an incident.

Interestingly, statistics show that women make up more mobile app users than males—68% versus 30%. On the other hand, 58% of website visitors are men, and 42% are women. In the context of one-way ANOVA, the results show that the value of all the website features is only related to the frequency and purpose of the trip. Concerning the mobile app, the passenger's gender and the frequency of their trip are found to be related to five of its eight features. Moreover, it is observed that the trip frequency is related to the ease of use, the data reliability, and the possibility of defining ticket costs for both channels. According to the SEM results of our study, the information channels significantly impact overall satisfaction.

Interestingly, this result aligns with those of [90,91], who observed that website design, website reliability, and responsiveness influence passenger satisfaction (travel website and airline industry) in their study focused on the relationship between website quality dimensions on passenger satisfaction. Also, our results show that improving the quality of the website and application influences overall satisfaction. It is observed that the model's fit increases when a relationship between the ticket price and the information channels (as a mediation) is considered.

The direct effect of information channels on satisfaction, mediated through ticket price perceptions, introduces a novel insight into the role of digital interfaces in the passenger experience. This finding contributes to the burgeoning literature on the digital transformation of public transport services, suggesting that information channels serve as tools for information dissemination and as integral components of the service value.

6.4. SEM-ANN Model

The model shows that the attributes of travel experience, information channels, and ticket price positively influence passenger satisfaction. Among the latent variables that significantly affect overall satisfaction in the SEM model, the ticket price is shown to be the strongest predictor of overall satisfaction in the ANN model. This shows that passenger satisfaction increases when they perceive that the fare is adequate for the services received.

The analysis of the ANN results shows that ticket price is the most important predictor of passenger satisfaction. However, there are dichotomous comments in the literature, with some indicating the importance of ticket price on passenger satisfaction [27,28], while others report little or no effect [17]. In contrast to previous studies that found no or small effects, in this study, we demonstrate that intercity bus fare, as the most important predictor, has a significant effect on passenger satisfaction. This might be explained by the variety of fares available, which depend on the services included. Having the possibility to choose between different fares, together with the feeling of receiving a fair service for the price, influences passenger satisfaction.

These findings have practical implications for bus operators and policymakers. The clear impact of the ticket price on satisfaction suggests that pricing strategies should be carefully considered, potentially incorporating flexible pricing models or discounts to enhance perceived value.

Because the information channels' latent variable and the application of the combined SEM-ANN methodology have not been applied to any study on passengers' satisfaction with intercity bus services, each path in the model SEM and its predictive function in SEM-ANN is discussed below:

The SEM results show that the information channels influence customer satisfaction. Our results show that website and application services are critical to passengers' satisfaction. The results of the ANN analysis show that the information channel is the second most important predictor of satisfaction, and travel experience is the third one. This result is in accordance with prior research, which indicates that travel experience has a positive impact on passenger satisfaction [92,93]. One noteworthy point is that because these previous studies could not rank the relative importance levels of predictor input variables, this research reveals that although travel experience is crucial in passenger satisfaction, it comes after ticket price.

7. Conclusions

Passenger satisfaction is crucial in the bus service sector, with companies continuously improving service quality and assessing the relationship between satisfaction and service attributes to identify key drivers. This study uses a hybrid SEM-ANN methodology to investigate passenger satisfaction in the intercity bus service sector, focusing on the Madrid–Bilbao route, providing a comprehensive understanding of passenger satisfaction dynamics. The distance of 398 km between the two cities falls within a typical range for intercity bus routes in Spain and Europe (medium distance [300–1000 km]) [94], allowing for the observations of this study to be extrapolated to different bus routes.

Our findings provide a holistic approach to providing important information for operators and policymakers. The goal is to foster a more satisfactory and competitive intercity bus service that considers immediate customer needs and aligns with environmental, social, economic, and sustainability criteria.

- Develop and Implement Fair Pricing Guidelines: This study emphasizes the impact ticket prices have on passenger satisfaction. To solve this and take corporate revenue into account, we should consider implementing fair dynamic pricing mechanisms. This can entail specific rules accurately representing the value provided, like price ceilings, early bird discounts, and tiered pricing for certain clientele groups.

Our findings underscore the multifaceted nature of satisfaction determinants and serve us to provide the following strategic insights for service enhancement:

- Invest in Quality Improvement in Travel Experience: We have observed that travel experience attributes such as punctuality, safety, and customer service have a considerable impact on passenger satisfaction, showing the need for extra investment in these areas. Operators might need to establish standards to measure and monitor these attributes in order to exceed certain benchmarks to meet passengers' expectations.
- Foster Digital Transformation in the Service: Our study underscores the pivotal role of digital platforms in enhancing passenger satisfaction. Decision-makers should promote funding initiatives or incentives for operators to upgrade their digital infrastructure. This upgraded version should at least offer ticketing options, provide real-time information, and ease customer–company interaction. These technologies should be able to make services more accessible and reliable through user friendly platforms designed based on users' needs.
- Address Service Quality Gaps: Targeted improvements are needed in areas such as lost/found services, baggage handling, and ease of customer interaction. Operators need to implement feedback mechanisms to identify service weaknesses. Regular monitoring together with this feedback can ensure that minimum service standards are accomplished.

Future research should explore socioeconomic characteristics, information channels, travel experience strategies, cross-cultural preferences, new technologies, and a comprehensive satisfaction model. Though this research focuses on using an ANN to increase customer satisfaction in public transit, artificial intelligence-driven strategies such as AC microgrids could be investigated to improve essential infrastructure resilience. The study conducted by Sahoo et al. [95] presents an event-driven technique that shows how artificial intelligence (AI) can be used for anomaly identification and adaptive responses.

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Appendix A

TRACKBEST-3S Project - Bus operation improvement

WELCOME

ALSA and the Polytechnic University of Madrid are working together in the TRACKBEST-3S project, funded by the Ministry of Science and Innovation to improve the information and quality of the bus service. Among the actions of this project is the development of a management tool to improve service reliability, environmental sustainability and reduce accidents. In order to tailor this tool to your needs, we ask you to answer this questionnaire about your travel habits and your satisfaction with the service.

Your opinion is very important!

You will participate in the DRAW of 3 Smart Box "Two days with charm" among the participants who complete the survey.

Clicking "Next" will take you to the questionnaire, which lasts approximately 10 minutes.

In compliance with the provisions of Organic Law 3/2018, of December 5, on the Protection of Personal Data and Digital Guarantees, we inform you that the personal data you provide in this form will be used for purposes ONLY related to the objectives of the TRACKBEST-3S project, exempt from commercial purposes.

Thank you very much for your help!

TRACKBEST-3S Project - Bus operation improvement

CARD NUMBER

The winner of the prize will be announced with the SURVEY NUMBER that appears on the card that has been given to him/her. You must keep the card in order to collect the prize.

N1 Enter the SURVEY NUMBER that appears on the card that was given to you.

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PERSONAL DETAILS

Next, we will ask you some personal characteristics to characterize the users of the transport services operated by ALSA.

S1 Current employment status

- Student
- Worker (Employee/Employer)
- Household worker
- Unemployed
- Retired
- Others

S2 Level of education completed

- Primary
- High school degree
- Bachelor
- University degree
- Others

S3 I have...

- ☐ Driving license
- ☐ Own car
- ☐ Motorcycle or moped
- ☐ Own bicycle
- ☐ Public transport card
- ☐ None of them

S4 Age (years)

S5 Gender

- Woman
- Man
- I prefer to not specify

C1 Rate from 1 to 5 the importance of the following factors for bus use

	Not important -1-	2	3	4	Very important -5-
Punctuality/Reliability					
Duration of trip					
Ticket price					
Connection with other mode transporte					
Safety					
Accessibility for reduced mobility people (RMP)					

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CHARACTERISTICS OF YOUR TRIP WITH ALSA

In this section of the survey we will ask you about the characteristics of your trip with ALSA.

CA1. What mode of transportation did you use to get to the bus station?

- ☐ Metro
- ☐ Suburban rail
- ☐ Interurban bus
- ☐ Urban bus
- ☐ Taxi
- ☐ Car as driver
- ☐ Car as passenger
- ☐ Motorbike
- ☐ Bicycle
- ☐ Walking
- ☐ Other

CA2. What mode of transportation did/will you use after getting off the bus to reach your final destination?

- ☐ Metro
- ☐ Suburban rail
- ☐ Interurban bus
- ☐ Urban bus
- ☐ Taxi
- ☐ Car as driver
- ☐ Car as passenger
- ☐ Motorbike
- ☐ Bicycle
- ☐ Walking
- ☐ Other

CA3 Select the origin and destination of your trip

- Madrid - Lerma
- Madrid - Burgos
- Madrid - Bilbao

CA4 How often do you make this trip?

- 1 or 2 times a week
- Few times a month
- Occasionally

CA5 What was the main reason for the trip in which you received the survey card?

- Work
- Study
- Leisure
- Other

CA6 Indicate the type of ticket you used for your travel

- Single
- Round trip
- Frequent voucher
- Other

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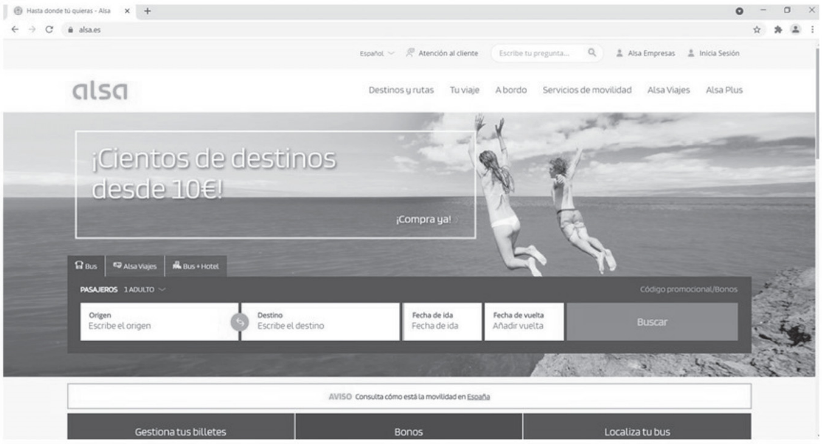
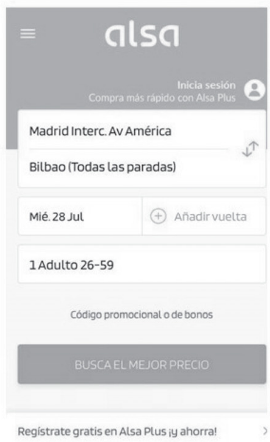
ALSA WEB AND APPLICATION

In this part we will collect your opinion about ALSA's application and website for the management of your trips.





AW1 Select which means you most frequently use to plan your bus trips

- ALSA application
- ALSA website
- Other

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ALSA website

AW2 Rate from 1 to 5 the degree to which you agree with the following statements related to ALSA's web site

	Strongly Agree -1-	-2-	-3-	-4-	Strongly Disagree -5-
Easy to use	○	○	○	○	○
Reliable data provided by the mobile app or web	○	○	○	○	○
Always up to date	○	○	○	○	○
Obtain real-time information on bus occupancy	○	○	○	○	○
Access information related to tickets purchase	○	○	○	○	○
Immediate response to incidents	○	○	○	○	○
Define preferences about the cost of my trip	○	○	○	○	○
Define preferences about the duration of my trip	○	○	○	○	○

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ALSA application

AW2 Rate from 1 to 5 the degree to which you agree with the following statements related to the ALSA application

	Strongly Agree -1-	-2-	-3-	-4-	Strongly Disagree -5-
Easy to use	○	○	○	○	○
Reliable data provided by the mobile app or web	○	○	○	○	○
Always up to date	○	○	○	○	○
Obtain real-time information on bus occupancy	○	○	○	○	○
Access information related to tickets purchase	○	○	○	○	○
Immediate response to incidents	○	○	○	○	○
Define preferences about the cost of my trip	○	○	○	○	○
Define preferences about the duration of my trip	○	○	○	○	○

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SERVICE PROVIDED BY ALSA

Next, we will ask you some questions about the service provided by ALSA.

SA1 Have you had any negative experiences with the bus service in the last 12 months?

○ Yesí

○ No

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SA2 Which one?

- ☐ Delay in bus de.parture time
- ☐ Delay in bus arrival time
- ☐ Problems with other passenger(s)
- ☐ Problems with luggage
- ☐ Lack of information
- ☐ Bad attention from the driver
- ☐ other (specify)

SA3 Rate from 1 to 5 the following attributes related to the service provided:

	Very bad -1-	2	3	4	Very good -5-	N/C
Ticket prices						
Variety of fare types						
Ease of purchasing tickets						
Information inside the bus						
Accessibility						
Heating and air conditioning						
Correct and adequate information						
Appearance and image of the driver						
Smoothness in driving (curves, braking)						
Duration of trip						
Time of access to the bus						
Punctuality of departure						
Customer Service user						
Notifications of incidents in the service						
Lost/found service						
Ease of contact with the company						
Sense of safety during the trip						
Security and baggage control						

SA4 Rate your general satisfaction with the services provided by ALSA

SA4 Would you recommend ALSA services to a friend or colleague?

No, not at all -1-	-2-	-3-	-4-	Yes, totally -5-

SA5 Do you consider that ALSA services are safe from a health point of view?

No, not at all -1-	-2-	-3-	-4-	Yes, totally -5-

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S5 Do you have children under 5 years of age in your care?

- Yes
- No

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S6 7 Would you be willing to pay an extra fee for a carrycot or special seat for baby/child?

- Yes
- No

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S6 Your net household income per month is:

- Less than or equal to €1,300
- Between €1,300 and €2,500
- Equal or greater than €2,500

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END OF THE QUESTIONNAIRE

THANK YOU VERY MUCH FOR YOUR HELP!

If you want to participate in the raffle for 3 Smart Box "Two days with charm" we would need an email.

THANK YOU VERY MUCH FOR YOUR TIME

Email confirmation:

Do you want to receive information on the aggregate results of the responses received?

- Yes
- No

If you wish, you can leave a comment

THANK YOU SO MUCH!

It is helping to improve bus services and their sustainability

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