



## Research paper

## An importance-performance analysis of public transport to the university campus based on best-worst scaling

Javier Hernán Matas-Monroy<sup>a,\*</sup>, Juan Carlos Martín<sup>b</sup>, Concepción Román<sup>b</sup><sup>a</sup> Universidad de Las Palmas de Gran Canaria, Institute of Tourism and Sustainable Economic Development, Spain<sup>b</sup> Universidad de Las Palmas de Gran Canaria, Institute of Tourism and Sustainable Economic Development, 35017, Las Palmas de Gran Canaria, Spain

## ARTICLE INFO

## Keywords:

Public transport  
University students  
Campus mobility  
Best-worst scaling  
Importance-performance analysis  
Discrete choice models

## ABSTRACT

University campuses represent important transport attraction poles in cities due to the large number of students, faculty and administrative staff who commute to the campus daily. The campus location can significantly increase traffic around the area, especially during the class entry and exit times. Therefore, public transport systems are essential to facilitate access to the university campus worldwide, especially for students. This study aims to evaluate the level of importance and satisfaction with factors that affect public transport use among university students. In this context, a best-worst scaling experimental design is used to carry out an importance performance analysis (IPA) of public transport services to university campuses in Gran Canaria by estimating a Mixed Logit model. Thus, it will be possible to determine what attributes should be prioritised when implementing policies for improving these services. The results showed that public transport managers and university authorities should primarily focus on providing direct services and improving punctuality and bus frequency. Our results also provide valuable insights into the search for the best policies that match students' transport mobility preferences with the service provision.

## 1. Introduction

During peak traffic periods, specific locations such as university campuses or hospitals function as major trip attractors in urban areas. University campuses, in particular, may be situated either within densely populated urban areas or on the periphery of cities. This dual positioning can create significant congestion challenges, often impacting the wider community beyond the immediate campus environment. Accessibility to university campuses primarily depends on the locations of the campuses and the residences of students, as well as the administrative and teaching staff. These factors shape the patterns of trips related to the university. Additionally, the surrounding land use and affordable housing in the area also play a role in determining accessibility.

University campuses often form multifaceted relationships with their surrounding urban and regional environments (Mohammed et al., 2022). Historically, some campuses have been established within city centres or historic districts, benefiting from proximity to diverse services and amenities. These central locations typically encourage short-distance trips, which are well-suited to active transport modes

such as walking, cycling, or using scooters (Caulfield et al., 2021). Other campuses have been developed in some peripheral neighbourhoods, for which active transport modes are not a valid alternative for most of the population visiting the campuses. Thus, it is evident that transport mode access to university campuses is highly context-dependent.

Universities worldwide have taken different travel demand management (TDM) initiatives, seeking to obtain more balanced and sustainable transport modal shares. This is especially relevant in car-dependent countries (Liu et al., 2023). In search of solutions, public transport and mobility-university authorities usually coordinate efforts to provide an adequate accessibility level to university campuses. Campus public transport access is more sustainable than private car access, but its choice depends on the level of service. Campus commuting choices using different transport modes that include more sustainable alternatives like walking, biking and public transport have been studied in the past. However, the method of improving public transport for university students has not yet been analysed.

This study explores which aspects should be prioritised to improve public transport access to university campuses as the primary policy, given that other measures—particularly those involving shared or active

\* Corresponding author.

E-mail addresses: [javier.matas101@alu.ulpgc.es](mailto:javier.matas101@alu.ulpgc.es) (J.H. Matas-Monroy), [jcarlos.martin@ulpgc.es](mailto:jcarlos.martin@ulpgc.es) (J.C. Martín), [concepcion.roman@ulpgc.es](mailto:concepcion.roman@ulpgc.es) (C. Román).<https://doi.org/10.1016/j.retrec.2025.101519>

Received 8 March 2024; Received in revised form 13 January 2025; Accepted 15 January 2025

Available online 24 January 2025

0739-8859/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

transport modes—have not been widely developed by universities when campuses are far from urban centres. Carpooling and ridesharing options are often hindered by personal concerns, such as managing conflicting family commitments or maintaining individualised schedules (Logan et al., 2020). Similarly, the adoption of active transport modes is sometimes limited by the geographical location of campuses. Consequently, the research emphasises PT as a critical backbone of the available TDM strategies.

The analysis is particularly pertinent in light of the unique challenges posed by the COVID-19 pandemic. Encouraging students to resume using PT required targeted interventions, such as awareness campaigns, fare discounts, or temporary fare exemptions. Furthermore, it was essential to disseminate clear information on health and safety measures implemented by authorities to ensure a COVID-safe PT environment.

The aim of this paper is to evaluate the importance and satisfaction levels of key attributes influencing public transport usage among university students. To achieve this, we propose a refined Discrete-Choice-Importance-Performance Analysis (DC-IPA) methodology (Martilla & James, 1977), addressing several limitations of traditional IPA approaches based on averaged scores obtained from standard surveys where the attributes are independently evaluated using certain measurement scales. The research focuses on enhancing public transport services for university campuses in Gran Canaria, prioritising policies through an innovative evaluation framework. Our methodology integrates established and novel techniques to comprehensively analyse PT service attributes in the Canary Islands. First, we employ a best-worst scaling (BWS) experimental design, which captures student preferences more precisely than conventional surveys by identifying the relative trade-offs and priorities among attributes (Louviere & Woodworth, 1990). This approach provides a nuanced understanding of the factors students value most. Second, we extend the insights from the BWS experiment into an enhanced IPA framework by estimating an underlying discrete choice model. In addition, the method addresses common challenges associated with Likert or other semantic scales, such as varying interpretations of scale labels and the limited cognitive ability to differentiate between categories.

The remainder of this document is structured as follows: Section 2 provides a comprehensive literature review on topics related to university students and the development of scales to evaluate the importance and satisfaction of PT. Section 3 outlines the methodology employed in the analysis. Section 4 presents the results and offers a detailed discussion. Finally, Section 5 highlights the primary conclusions and discusses the study's limitations.

## 2. Literature review

The presence of university campuses offers a valuable opportunity to implement and evaluate transport demand management (TDM) initiatives aimed at fostering more balanced and sustainable travel behaviours. Mulley and Reedy (2016) highlighted the significant potential of university-based TDM measures to influence the commuting choices of tens of thousands of individuals. The distribution of travel patterns is closely tied to both the implementation of these initiatives and the geographic location of campuses.

Universities serve as engines of innovation, driving the need for advanced facilities such as state-of-the-art laboratories, high-performance computing centres, and aquaculture tanks. These resources are essential for groundbreaking research and preparing students with the skills necessary for success. However, limited and expensive urban real estate constraints often make it challenging to house such sophisticated infrastructure. Expanding to the outskirts gives universities the space required to build modern research facilities. This expansion, in turn, sparks peripheral urban transformation, giving rise to new neighbourhoods and transport hubs tailored to the needs of students and staff (Mohammed et al., 2022).

Despite its advantages, this trend introduces a significant challenge:

providing swift and frequent public transit in the low-density areas typical of urban peripheries. Vuchic (2017) likens this difficulty to spreading a thin layer of peanut butter—ridership in such areas is sparse and dispersed. Low population density makes frequent public transit services financially unsustainable, while the longer routes required to serve these regions increase travel times, deterring potential riders. This creates a vicious cycle: low ridership leads to reduced service, further decreasing ridership. To break this cycle, university authorities must explore innovative transit solutions that go beyond simply replicating the dense networks of urban centres. Creative strategies tailored to the unique challenges of suburban settings are essential to ensure accessibility and sustainability.

Universities exhibit unique characteristics regarding their transportation needs and challenges. University authorities often prioritise the creation of green, walkable campuses that foster academic collaboration and community interaction in the trips generated internally. However, parking lots pose significant challenges, as they occupy valuable space and contribute to congestion. Unlike other urban areas, universities display distinct daily commuter flow patterns, influenced by class schedules that create multiple peak hours for student arrivals and departures.

Many universities have implemented comprehensive initiatives to promote sustainable transport modes to address environmental concerns and reduce car dependency. Various studies have examined policies incorporated within these initiatives, including parking restrictions (Bond & Steiner, 2006), parking pricing (dell'Olio et al., 2019), and non-price PT improvements (Bond & Steiner, 2006). Additional measures include fare-free PT tickets (Brown et al., 2003), PT subsidies (Rotaris & Danielis, 2015), shared-ride taxi services (Ayyash et al., 2016), and active transport promotion (Logan et al., 2020). Further strategies encompass carpooling programs (Ashraf Javid & Al-Khayyat, 2021), bike-sharing systems (Ribeiro & Fonseca, 2022), car-sharing initiatives (Rotaris et al., 2019), and integrated mobility solutions such as mobility-as-a-service (Esztergár-Kiss & Kerényi, 2022; Matyas & Kamargianni, 2021).

Aligned with global sustainability goals, universities worldwide increasingly promote public transport, particularly bus services, as a sustainable and environmentally friendly means of campus access. This emphasis acknowledges the complexity of trip origins and the challenges posed by some campus layouts and surrounding infrastructure, which can limit the feasibility of walking, cycling, or other micro-mobility options. To address these issues, University Mobility Directorates prioritise public transport as a core component of their TDM strategies, aiming to provide a convenient, accessible, and eco-friendly commuting solution for both students and faculty.

Numerous studies have explored the factors influencing public transport (PT) usage among university populations. Romanowska et al. (2019) demonstrated that students are more likely to use public transport than university staff, citing factors such as car availability, trip origin, and accessibility as key determinants of transport mode choice. Their findings reveal that while 57% of staff primarily rely on private cars, 59% of students predominantly use public transport. These disparities have been corroborated by other studies, including those by Logan et al. (2020), Myftiu et al. (2024), Ribeiro et al. (2020), and Pérez-Neira et al. (2020), which have reported similar or even more pronounced asymmetries.

A critical factor influencing the adoption of public transport is the perceived quality of service. This multifaceted concept encompasses attributes such as reliability, frequency, cleanliness, safety, and affordability, all shaped by the efforts of planning authorities and transport operators (Balcombe et al., 2004). While numerous service attributes exist, research highlights the benefits of grouping them into core dimensions for improved analysis and comprehension (de Oña & de Oña, 2015). Moreover, service quality is recognised as a multilevel construct, influenced by system-level factors (e.g., network design, vehicle condition), service encounter-level elements (e.g., driver behaviour,

availability of information), and individual-level perceptions (e.g., personal needs, expectations) (Jen et al., 2011; Parasuraman et al., 1985).

Enhancing public transportation requires methodologies that delve deeper into understanding passenger needs and preferences. Regular passenger surveys and feedback-focused group sessions are essential for gathering such insights. When combined with monitoring key performance indicators (KPIs) such as punctuality, reliability, and accident rates, this data provides a comprehensive framework for evaluating service effectiveness. A widely adopted approach in these surveys is the IPA method, which assesses service quality through a two-dimensional lens of importance and satisfaction for various attributes (Martilla & James, 1977).

Following an extensive literature review and an in-depth examination of the target market—university students—we identified a set of attributes relevant to our study, as summarized in Table 1. These attributes span several dimensions of public transport service quality, including transport services, vehicle quality, overall service level, information and communication technologies (ICTs), and bus stop quality. Recognizing the significant role that ICTs play in transport systems due to their diverse functions (Gössling, 2017), especially in the young population segment like university students, the current study introduced two additional items that were not addressed in previous research. In addition, given the impact of the COVID-19 pandemic, health and safety considerations, such as facemask mandates—whose effectiveness in public transportation during the pandemic has been analysed (Grzybowska et al., 2022; Ku et al., 2021)—have also been incorporated.

By leveraging these evidence-based measures, universities and public transport authorities can design systems that are more accessible, convenient, and appealing to students. The resulting improvements will likely increase ridership, reduce traffic congestion, and foster a more sustainable transportation ecosystem in and around university campuses.

### 3. Materials and methods

#### 3.1. Case study, survey and data collection

The University of Las Palmas de Gran Canaria has four campuses spread over the island. The main campus is in Tafira, 10 km from Las Palmas de Gran Canaria city centre. Las Palmas de Gran Canaria is the most populated city of the Canary Islands archipelago, with 378,027 inhabitants in 2023. The Mobility Report of the University of Las Palmas de Gran Canaria (2022) showed that the two most representative access transport modes used by students were public transport (60.7 %) and private car drivers (26.0 %). Thus, the analysis of public transport in the context of university students is crucial to enhance their experience by providing different areas of policy intervention to public transport managers and university authorities.

Data for this study were collected through a survey administered to University of Las Palmas de Gran Canaria students in March 2023. The questionnaire was structured into four sections. The first section gathered information about the travel characteristics, including frequency of public transport (PT) use and the total trip duration. The second section focused on the best-worst experiment, which will be detailed in the next section. The third part involved evaluating the importance and satisfaction levels associated with the various attributes incorporated into our study using a 5-point semantic scale. Finally, the fourth section of the questionnaire collected socioeconomic information.

With the assistance of the university's sustainability department, we distributed the online questionnaire to all students via the Google Forms platform. A preliminary screening question ensured that participation was limited to students who had used PT to reach the campus at least once during the current academic year. After a thorough data-cleaning process to identify and eliminate invalid or incomplete responses, the

**Table 1**  
Public transport attributes.

	Attributes	Source	Category
1	Price	Beck and Rose (2016); De Oña et al. (2012)	Transport service
2	Travel time	Allen et al. (2019); Beck and Rose (2016); De Oña et al. (2012); Grisé and El-Geneidy (2017); Tavares et al. (2021); Allen et al. (2019); Beck and Rose (2016); De Oña et al. (2012)	
3	Bus frequency	Allen et al. (2019); Beck and Rose (2016); De Oña et al. (2012)	
4	Punctuality	Beck and Rose (2016); De Oña et al. (2012); Grisé and El-Geneidy (2017); Tavares et al. (2021)	
5	Ease of transfers	Allen et al. (2019); Beck and Rose (2016)	Vehicle quality
6	Availability of a direct service to the campus	Yen et al. (2017)	
7	Temperature inside the bus	Allen et al. (2019); Beck and Rose (2016); De Oña et al. (2012); Beck and Rose (2016); Grisé and El-Geneidy (2017); Tavares et al. (2021)	
8	Seat comfort	Allen et al. (2019); De Oña et al. (2012); Grisé and El-Geneidy (2017)	
9	Reinforced security with surveillance cameras on the bus	Beck and Rose (2016); Allen et al. (2019); De Oña et al. (2012); Grisé and El-Geneidy (2017)	General level of service
10	Cleanliness of the bus	Beck and Rose (2016); Allen et al. (2019); De Oña et al. (2012); Grisé and El-Geneidy (2017)	
11	Noise level inside the bus	Allen et al. (2019); Beck and Rose (2016); Grisé and El-Geneidy (2017)	
12	Possibility of being seated during the trip	Beck and Rose (2016)	
13	Friendliness of the driver	Beck and Rose (2016); Grisé and El-Geneidy (2017)	ICTs
14	Driver's driving style	Grisé and El-Geneidy (2017)	
15	Ease of access for people with mobility problems	Authors' proposal	
16	Possibility to pay with smart devices (mobile phone, smartwatch)	Authors' proposal	
17	Availability of USB chargers inside the bus	Authors' proposal	Bus stop quality
18	Availability of information panel at bus stops with estimated waiting time	Allen et al. (2019); De Oña et al. (2012); Grisé and El-Geneidy (2017); Tavares et al. (2021)	
19	Availability of real-time information panel on upcoming bus stops on the bus	Allen et al. (2019); De Oña et al. (2012); Grisé and El-Geneidy (2017); Tavares et al. (2021)	
20	Availability of a mobile app facilitating estimated waiting time at each stop	Beck and Rose (2016); Mulley et al. (2017)	
21	Availability of shelter and seating at bus stops	Beck and Rose (2016); Grisé and El-Geneidy (2017)	Health safety
22	Nearby location of bus stops	Beck and Rose (2016); De Oña et al. (2012)	
23	Cleanliness of bus stops	Beck and Rose (2016); Grisé and El-Geneidy (2017)	
24	Existence of air renewal filters	Allen et al. (2019); Grzybowska et al. (2022); Ku et al. (2021)	
25	Obligation to wear a mask if it is determined that there is a risk of contagion	Grzybowska et al. (2022); Ku et al. (2021)	

Source: Own elaboration

final sample was 477 participants. To estimate the sampling error, we considered two scenarios given the uncertainty regarding the population size of students using public transportation for their campus commute. Based on the 2022 mobility survey conducted by the University of Las Palmas de Gran Canaria (ULPGC, 2022), the first scenario assumed that 60.7% of the total student population (17,751) relied on public transport. The second scenario, obtained from our survey, postulated that 91% of students had used public transportation at least once during the academic year. Based on these assumptions, the sampling error was calculated to fall within a range of 4.37%–4.42%.

### 3.2. Best-worst scaling experimental design

Best-worst scaling (BWS) represents a compelling data collection method for eliciting preferences, particularly in the realm of discrete choice analysis. It was first introduced by Louviere and Woodworth (1990) and consists of choosing the most and least preferred option from a finite set of alternatives. By doing this, the individual selects the two objects from a varying set of three or more options that exhibit the most significant perceptual discrepancy (Finn & Louviere, 1992). Thus, the choice frequencies across the different scenarios provide the information to estimate the relative values of each attribute.

Different authors have pointed out several advantages of this method. In this regard, Potoglou et al. (2011) highlight that the method reduces respondents' cognitive burden while providing more information than traditional "pick-one" tasks commonly employed in discrete choice experiments. Moreover, a comparative analysis between BWS and ordered probit/logit models reveals comparable results in a specific case study, while BWS emerges as the more cost-effective approach (Echaniz et al., 2019). In addition, the method is free of the biases found in standard response scales, making it adequate for comparing many attributes (Beck & Rose, 2016).

Depending on the complexity of the items to be analysed, there are three ways of presenting the options in the choice tasks of a BWS experiment. In BWS Case 1 – Object Case, options are represented by lists of objects. In BWS Case 2 – Profile Case, options are defined by combinations of attribute levels within a single alternative. In BWS Case 3 – Multi-Profile Case, options are sets of alternatives akin to a typical discrete choice experiment (Louviere et al., 2013). A comprehensive guide to understanding the various BWS methods is provided by Louviere et al. (2015).

The experimental design used in this research concentrates on the BWS case 1, where the goal is to evaluate the set of attributes (objects) of the PT service listed in Table 1 according to an underlying latent scale. The ultimate purpose is to obtain a prioritisation of these attributes in a latent scale of importance and satisfaction.

Various methods exist for constructing the choice tasks in BWS experiments for the object case. However, researchers must carefully consider the design of the experiment to avoid potential problems arising from using non-constant choice set sizes, which could lead respondents to make wrong assumptions about the relative importance of attributes. For example, individuals could think that those attributes appearing in small choice sets should be treated with more attention than others. The balanced incomplete block design (BIBD) has been pointed out by Louviere et al. (2015) as an efficient way of building the experiment choice tasks. BIBDs allow the researcher to control the number of objects included in the choice tasks that must be constant along the experiment, the number of times each object appears in the choice tasks, as well as the number of times each pair of objects appears together.

The choice scenarios in our experiment were created with the package "crossdess" and the function "findBIB" within the R statistical software environment (R Core Team, 2013). The design resulted in 30 choice tasks containing five attributes each. Each attribute appears six times across the choice tasks and co-occurs once with the others. The design was separated into three blocks to minimise respondents' burden,

each containing 10 choice tasks. The separation was carried out using a randomised procedure. Fig. 1 shows an example of a typical choice task in the experiment. Thus, given the attributes shown in the choice task, the individual must identify the one they consider most and least important, as well as the one they are most and least satisfied with. In this regard, it is important to note that the five options are to be regarded as the alternatives in the choice model and their interpretation in the experiment is limited to the order in which they are presented. Thus, in the choice task in Fig. 1, the alternative presented in second place (alternative 2) is represented by the attribute "Ease of access for people with mobility problems". Since each participant answered four-choice questions for each scenario, 40 observations were provided by a single respondent. Thus, 19,080 statistical observations were collected after completing the survey.

### 3.3. Discrete choice models to analyse BWS data

Discrete choice models have gained widespread recognition as a robust and versatile tool for analysing consumer preferences. They can be derived using the random utility maximisation paradigm, which assumes that individuals make rational decisions and always choose the option that maximises their utility. Considering that the modeller has imperfect information about consumers' preferences, the utility of an alternative is expressed as the sum of a systematic or deterministic component defined in terms of the characteristics of the alternative and the individual, as well as a random component that accounts for unobserved effects (McFadden, 1974). The specific assumptions made regarding the statistical distribution of the random component of the utility determine the choice probabilities of the various discrete choice models. The Multinomial Logit (MNL), Nested Logit (NL), Probit and those belonging to the Mixed Logit (ML) family are among the most widely used models (see Train (2009) for a comprehensive reference book).

Data obtained from BWS experiments can be analysed using a discrete choice model. Two critical considerations arise when analysing data containing multiple choices provided by the same individual: i) the potential correlation among choices made by a single respondent; and ii) the pseudo-panel nature of the data set by considering that preferences remain constant within a given respondent but could vary across individuals. These aspects can be addressed by the panel formulation of the error component ML model where the utility of alternative  $i$  for individual  $q$  in choice situation  $s$  is specified as:

$$U_{iqs} = V_{iqs} + \mu_{iq} + \varepsilon_{iqs} \quad (1)$$

where  $V_{iqs}$  is the systematic (or measurable) utility that is expressed in terms of the characteristics of the alternative;  $\varepsilon_{iqs}$  is an error term accounting for unobserved effects that distributes iid Gumbel  $(0, \beta)$ ; and  $\mu_{iq}$  is an error component, common to all observations of the same individual, that distributes Normal with zero mean and standard deviation  $\sigma$ ; with  $\mu_{iq}$  and  $\varepsilon_{iqs}$  being independent and  $\sigma$  representing the degree of correlation among choices made by the same respondent in the choice experiment.

There are several approaches to deal with best-worst data in discrete choice modelling. The one used in this study is based on the assumption that choices are made sequentially and that choosing the worst option is equivalent to maximising the negative of the utility of the alternatives included in the choice set, that is,  $\text{Min}_j\{U_j\} = \text{Max}_j\{-U_j\}$ . When the best-choice task is presented first, the worst alternative must be chosen from the remaining set of options. This model is discussed in Flynn and Marley (2014) and is commonly referred to as the "first best, then worst" paradigm. It is important to highlight that results could differ from those obtained when the "first worst, then best" approach is used. For a more in-depth and insightful exploration of sequential best-worst choices in discrete choice experiments, Lancsar et al. (2013) present a thought-provoking discussion that delves into the intricacies of this



Alternative	Public transport attributes				
1	Friendliness of the driver				
2	Ease of access for people with mobility problems				
3	Availability of a mobile app facilitating estimated waiting time at each stop				
4	Nearby location of bus stops				
5	Obligation to wear a mask if it is determined that there is a risk of contagion				
Based on your experience taking the bus to campus, please indicate which attribute you consider the most and least important, and which you are most and least satisfied with.					
Most important	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Least important	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Most satisfied	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Least satisfied	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

Fig. 1. Example of choice task.

methodological approach.

Thus, considering a choice set of  $J$  alternatives, the probability that the alternative  $i$  is chosen as best and  $r \neq i$  is chosen as worst in choice scenario  $s$  by individual  $q$ , conditional on the vector of error components

$\mu_q = (\mu_{1q}, \dots, \mu_{Jq})$ , is given by:

$$P_{(ir)qs} = \frac{e^{V_{iqs} + \mu_{iq}}}{\sum_{j=1}^J e^{V_{jq} + \mu_{jq}}} \frac{e^{-(V_{rq} + \mu_{rq})}}{\sum_{j=1, j \neq i}^J e^{-(V_{jq} + \mu_{jq})}} \quad (2)$$

$Sat_{iks} = 1$  if attribute  $k$  is shown in alternative  $i$  in choice scenario  $s$ ; 0 otherwise

The five attributes presented in each choice task, like the one presented in Fig. 1, are identified as the choice alternatives needed to build the choice model that enables the investigation of the importance and satisfaction associated with the PT attributes examined in the experiment. To simultaneously estimate the importance and satisfaction coefficients, a model comprising ten alternatives is considered, where the satisfaction alternatives were not available for the importance choice task and vice versa.

The utility of the alternatives considered in the model is represented by the following equations, which have been simplified by eliminating the sub-index  $q$  associated with the individual. Thus, the utility of alternative  $i$  in choice scenario  $s$  associated to importance choices  $U_{Impis}$

In the same fashion, the utility of alternative  $i$  in choice scenario  $s$  associated to satisfaction choices  $U_{Sat_{is}}$  is defined as:

$$U_{Sat_{is}} = ASC_i + \sum_{k=1}^{24} \alpha_{Sat_k} * Sat_{iks} + \mu_{Sat} + \varepsilon_{is} \quad i = 1, 2, 3, 4, 5 \quad (4)$$

Where  $ASC_i$ ,  $\beta_{Imp_k}$ ,  $\alpha_{Sat_k}$  and the standard deviations  $\sigma_{Imp}$  and  $\sigma_{Sat}$  of the error components  $\mu_{Imp}$  and  $\mu_{Sat}$  represent the unknown fixed model coefficients. The utility specification includes the 24 dummy variables  $Imp_{iks}$  (or  $Sat_{iks}$ ) defined above, with the last attribute in Table 1 acting as a reference. Therefore, for each observation in the data set, the utility of the first alternative (for example) would be explained by the constant term ( $ASC_1$ ) and the attribute appearing first in the choice task, as the dummies corresponding to the rest of the attributes are set to zero.

The contribution of the individual  $q$  to the likelihood function is represented by the joint probability  $P_q$  that individual  $q$  make the observed sequence of choices for both, importance and satisfaction, in best-worst choice tasks, that is given by

$$P_q = \int \int \prod_{s \in S} P_{(ir)^{*}imp_{qs}}(\beta_{imp}, \sigma_{imp}) P_{(ir)^{*}sat_{qs}}(\alpha_{sat}, \sigma_{sat}) f(\mu_{imp} | \sigma_{imp}) f(\mu_{sat} | \sigma_{sat}) d\mu_{imp} d\mu_{sat} \quad (5)$$

is represented by:

$$U_{Imp_{is}} = ASC_i + \sum_{k=1}^{24} \beta_{Imp_k} * Imp_{iks} + \mu_{Imp} + \varepsilon_{is} \quad i = 1, 2, 3, 4, 5 \quad (3)$$

Where,  $S$  represents the number of choice scenarios;  $(ir)^{*}imp_{qs}$  and  $(ir)^{*}sat_{qs}$  represent the choices made by individual  $q$  in choice scenario  $s$  in importance and satisfaction questions, respectively; and  $f$  is the Normal probability density function.

$Imp_{iks} = 1$  if attribute  $k$  is shown in alternative  $i$  in choice scenario  $s$ ; 0 otherwise

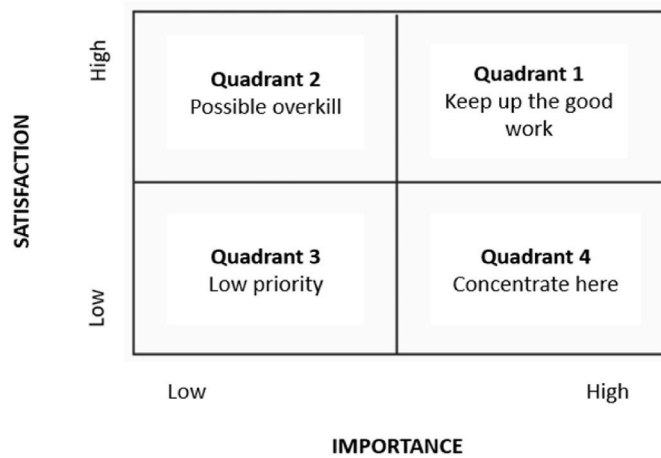


Fig. 2. The standard IPA chart.

Source: own elaboration (adapted from Martilla & James, 1977).

Thus, the log-likelihood function is represented by:

$$LL = \sum_q \ln(P_q) \quad (6)$$

Since the integrals in (5) cannot be solved analytically, simulation techniques are required to obtain the simulated likelihood function.

The coefficients in the utility functions represent the relative importance and satisfaction associated with each attribute, and the alternative specific constants,  $ASC_i$ , capture non-random unobserved factors that may influence individuals' choices. In this case, these are the order in which attributes are presented within the choice task (Beck & Rose, 2016). Additionally, the existence of panel correlation effects is determined by the significance of the standard deviation of the error components.

It is important to note that coefficients' sign can be either positive or negative, and their interpretation is inherently comparative, relying on the reference attribute as the benchmark. In our case, the reference variable is "Obligation to wear a mask if it is determined that there is a risk of contagion" (attribute number 25). Therefore, a positive coefficient for attribute  $k$  means that it is perceived as more important (or satisfactory) than attribute 25; whilst a negative coefficient indicates that it is less important (or satisfactory).

In this type of model, an attribute's significance level will also be interpreted in terms of the reference attribute. Thus, a low significance for the coefficient of attribute  $k$  means that its importance (or satisfaction) is not statistically different from that of the reference attribute (which can be interpreted as having a coefficient equal to zero).

### 3.4. Importance-performance analysis (IPA)

Importance-performance analysis (IPA), initially developed for marketing program evaluation (Martilla & James, 1977), has also found relevance in the transport sector. IPA has been employed to identify performance gaps between the importance of public transportation (PT) service attributes and their satisfaction levels (Esmailpour et al., 2020). The insights generated from IPA can guide policymakers in prioritising strategic interventions to enhance the customer experience by improving a particular service. IPA utilises a two-dimensional graph divided into four quadrants to classify attributes based on their performance and importance.

Fig. 2 shows an adaptation of the conventional IPA chart in which performance is associated with the satisfaction dimension. As illustrated, there can be four different situations concerning a specific attribute. Those located in Quadrant 1, "Keep up the good work", are attributes that present a high level of importance and a high level of

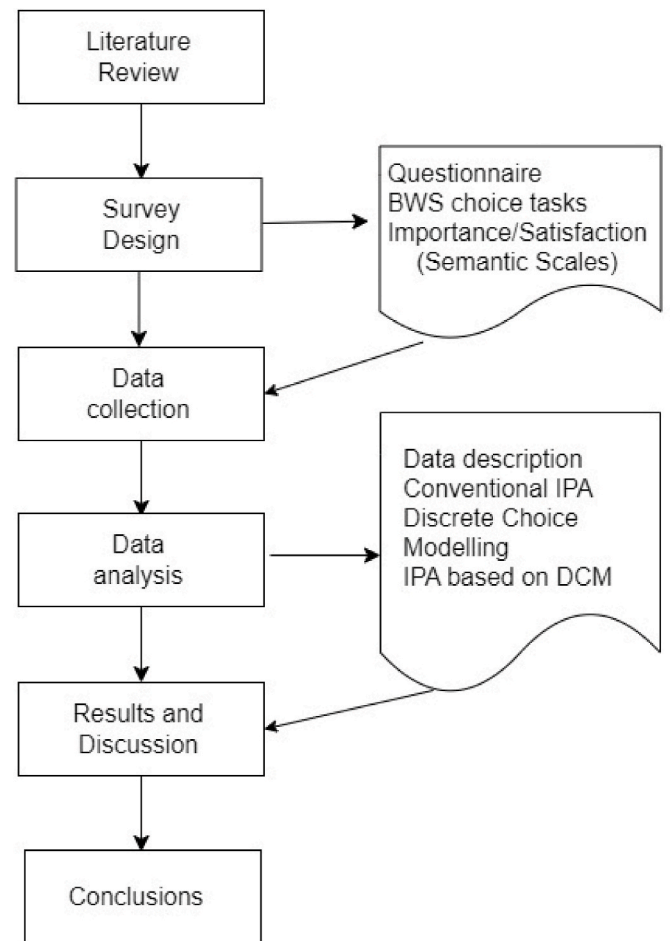


Fig. 3. Methodological flowchart.

Table 2

Sample descriptive statistics.

Usual transport mode for campus commuting		Sex	
Bus	85.12%	Male	37.90%
Car as driver	7.96%	Female	62.10%
Car as companion	3.98%	<b>Age</b>	
Bike	0%	Age (average)	21.8
Walking	2.31%	<b>Monthly net family Income</b>	
Other	0.63%	Less than 450 €	3.60%
<b>Frequency of use of bus transport</b>		From 450 to 900 €	11.30%
Daily	72.18%	From 901 to 1500 €	31%
3 or 4 times per week	22.41%	From 1501 to 2400 €	31%
1 or 2 times per week	4.41%	From 2401 to 3500 €	12.40%
Less than once per week	1%	From 3501 to 4500 €	6.30%
<b>Trip duration</b>		More than 4500 €	4.40%
Average travel time (minutes)	50.50	<b>Combining work with studies</b>	
<b>Use of bus if private transport were available</b>		Yes	12.20%
Yes	42.35%	No	87.80%
No	57.65%	<b>Academic programme currently enrolled in</b>	
		Bachelor	90.99%
		Master	5.45%
		PhD	3.56%

Source: Own elaboration

satisfaction. Attributes in this quadrant are considered essential to users and are currently meeting expectations. Policymakers should focus on maintaining these attributes to ensure continued satisfaction and loyalty. In Quadrant 2, "Possible overkill", attributes exhibit a high level of satisfaction but are considered unimportant. In this case, resources do not need to be committed to maintaining these attributes; rather, they should be monitored to ensure they remain satisfactory. The attributes in Quadrant 3, "Low priority", are neither important nor satisfactory to consumers. Thus, policymakers may consider redesigning these attributes to optimise resources and focus on more important areas for users. Finally, attributes in Quadrant 4, "Concentrate here", are those that customers find important and are not very satisfied with. Thus, policymakers should prioritise strategies to improve user satisfaction.

Fig. 3 shows the methodological flowchart of the study. It can be seen that the results of the conventional IPA model will be compared with the IPA based on the results obtained from the choice model to determine what attributes should be prioritised when implementing policies aimed at improving the public transport services to the university campus. In this regard, the model coefficients, after being appropriately normalised, will be used to calculate an index of importance and satisfaction for each attribute that will allow us to place each attribute in the IPA quadrants following the same logic of the conventional IPA model. In addition, the conventional IPA model will be applied to the scores obtained using the 5-point semantic scale of importance and satisfaction for the attributes.

## 4. Results and discussion

### 4.1. Sample description

Table 2 presents descriptive statistics for key survey responses. A substantial majority of respondents, approximately 85.12%, use PT to access their respective campuses. The choice of alternative sustainable modes, such as walking or cycling remains relatively negligible. Regarding the weekly frequency of use, a predominant percentage of individuals rely on bus transport to commute to their faculties daily, with only a marginal 1% using it less than once a week. As will be further explained in the following estimation results, travel time appears as a significant factor that has a considerable influence on the experience of travelling by public transport; in fact, the average travel time by PT to the various faculties is approximately 51 min. In addition, a significant proportion of PT users, approximately 76%, indicated that they have no alternative transport options available, suggesting they are captive users. Furthermore, nearly 58% of these captive users stated that they would switch to private transport if other options were available.

Regarding the socioeconomic information, the sample is slightly over-represented by females, with 62.10% of respondents identifying as such, compared to the overall proportion of women among university students, which is 58.20%. In this regard, it is important to note that gender distribution among the population under analysis is unknown, so it is difficult to anticipate whether this overrepresentation is due to online answering gender differences or to the fact that it is possible that female students can use public transport more often in our case. It was

**Table 3**  
BWS estimation results.

Attributes				Importance			Satisfaction		
Num	Name	Category	Estimate	t-test	p-val	Estimate	t-test	p-val	
1	Price	Transport service	1.75	19.35	0.00	1.29	14.95	0.00	
2	Travel time		1.93	21.18	0.00	−0.33	−3.93	0.00	
3	Bus frequency		3.22	33.21	0.00	−0.78	−9.23	0.00	
4	Punctuality		3.07	31.22	0.00	−0.54	−6.43	0.00	
5	Ease of transfers		1.64	17.51	0.00	−0.08	−0.92	0.36	
6	Availability of a direct service to the campus	Vehicle quality	3.03	31.23	0.00	−0.46	−5.31	0.00	
7	Temperature inside the bus		0.90	9.87	0.00	−0.06	−0.71	0.48	
8	Seat comfort		0.16	1.70	0.09	0.33	3.90	0.00	
9	Reinforced security with surveillance cameras on the bus		0.59	6.42	0.00	0.29	3.41	0.00	
10	Cleanliness of the bus		1.57	17.00	0.00	0.59	6.87	0.00	
11	Noise level inside the bus	General level of service	0.22	2.36	0.02	−0.07	−0.87	0.39	
12	Possibility of being seated during the trip		1.41	14.39	0.00	−0.08	−0.88	0.38	
13	Friendliness of the driver		0.60	6.80	0.00	0.62	7.36	0.00	
14	Driver’s driving style		1.36	14.08	0.00	0.24	2.71	0.01	
15	Ease of access for people with mobility problems		1.94	20.49	0.00	0.55	6.38	0.00	
16	Possibility to pay with smart devices (mobile phone, smartwatch)	ICTs	0.53	5.65	0.00	0.61	7.18	0.00	
17	Availability of USB chargers inside the bus		−0.31	−3.66	0.00	0.31	3.69	0.00	
18	Availability of information panel at bus stops with estimated waiting time		1.62	17.72	0.00	−0.13	−1.51	0.13	
19	Availability of real-time information panel on upcoming bus stops on the bus	Bus quality	1.20	12.85	0.00	−0.15	−1.74	0.08	
20	Availability of a mobile app facilitating estimated waiting time at each stop		1.55	16.51	0.00	0.22	2.58	0.01	
21	Availability of shelter and seating at bus stops		1.02	10.67	0.00	−0.12	−1.34	0.18	
22	Nearby location of bus stops		2.01	21.13	0.00	0.34	3.94	0.00	
23	Cleanliness of bus stops		0.43	4.73	0.00	0.05	0.58	0.57	
24	Existence of air renewal filters	Health safety	0.50	5.28	0.00	−0.11	−1.25	0.21	
25	Obligation to wear a mask if it is determined that there is a risk of contagion		0.00	(Fixed)	(Fixed)	0.00	(Fixed)	(Fixed)	
Error components									
Standard deviation (sigma)			0.59	12.75	0.00	0.39	7.75	0.00	
Alternative specific constants									
ASC1			0.55	16.97	0.00	−	−	−	
ASC2			0.30	9.06	0.00	−	−	−	
ASC3			0.26	8.02	0.00	−	−	−	
ASC4			0.29	9.10	0.00	−	−	−	
ASC5			0.00	(Fixed)	−	−	−	−	
Model information									
Number of observations			19080						
Number of individuals			477						
Null log-likelihood			−28579.29						
Final log-likelihood			−25093.32						

already mentioned that some studies found that females use public transport more often when accessing university campuses (Hamad et al., 2021). The average age of the respondents is approximately 22 years old. With regard to net household income, 62% of the sample falls within the range of 901–2400 euros per month. Moreover, as we focus on students, most individuals reported not combining work with their studies. Notably, almost all participants were enrolled in a bachelor's degree (91%), which is consistent with the figures reported by the University (88.9%).

#### 4.2. Estimation results

Model parameters were estimated using the simulated maximum likelihood method, implemented by the software Biogeme 2.2 (Bierlaire, 2009). Table 3 presents the parameter estimates for the BWS Mixed Logit model, described in Section 3.3. The table is structured into seven columns, corresponding to the attribute number and denomination (according to Table 1), their respective categories, and the estimates and t-tests for both importance and satisfaction parameters. Additional model information is provided in the last rows of the table. The alternative specific constants (ASCs) are specified in the first four alternatives

for both importance and satisfaction, with the fifth alternative acting as a reference. They account for the order effect in which the different attributes are presented in the choice task. In this regard, looking at the magnitude and sign of the coefficients, individuals are more likely to select the first four alternatives rather than the fifth one when the effect of the displayed attribute is not taken into account in the choice task. The interpretation of the importance and satisfaction values must be carried out with respect to the reference variable ("Obligation to wear a mask if it is determined that there is a risk of contagion").

Regarding importance estimates, all attributes except for "Seat comfort" were statistically different (at the 95% confidence level) from the reference attribute, "Obligation to wear a mask if it is determined that there is a risk of contagion". Of these attributes, only one, "Availability of USB chargers inside the bus", had a negative sign, indicating that it was less important than the reference attribute. The remaining attributes had positive signs, suggesting they were more important than the reference one.

Concerning the satisfaction results, 9 of the 24 attributes were not statistically different from "Obligation to wear a mask if it is determined that there is a risk of contagion". As for the sign of the coefficients, 12 of the 24 attributes present a negative sign, which means that the users are

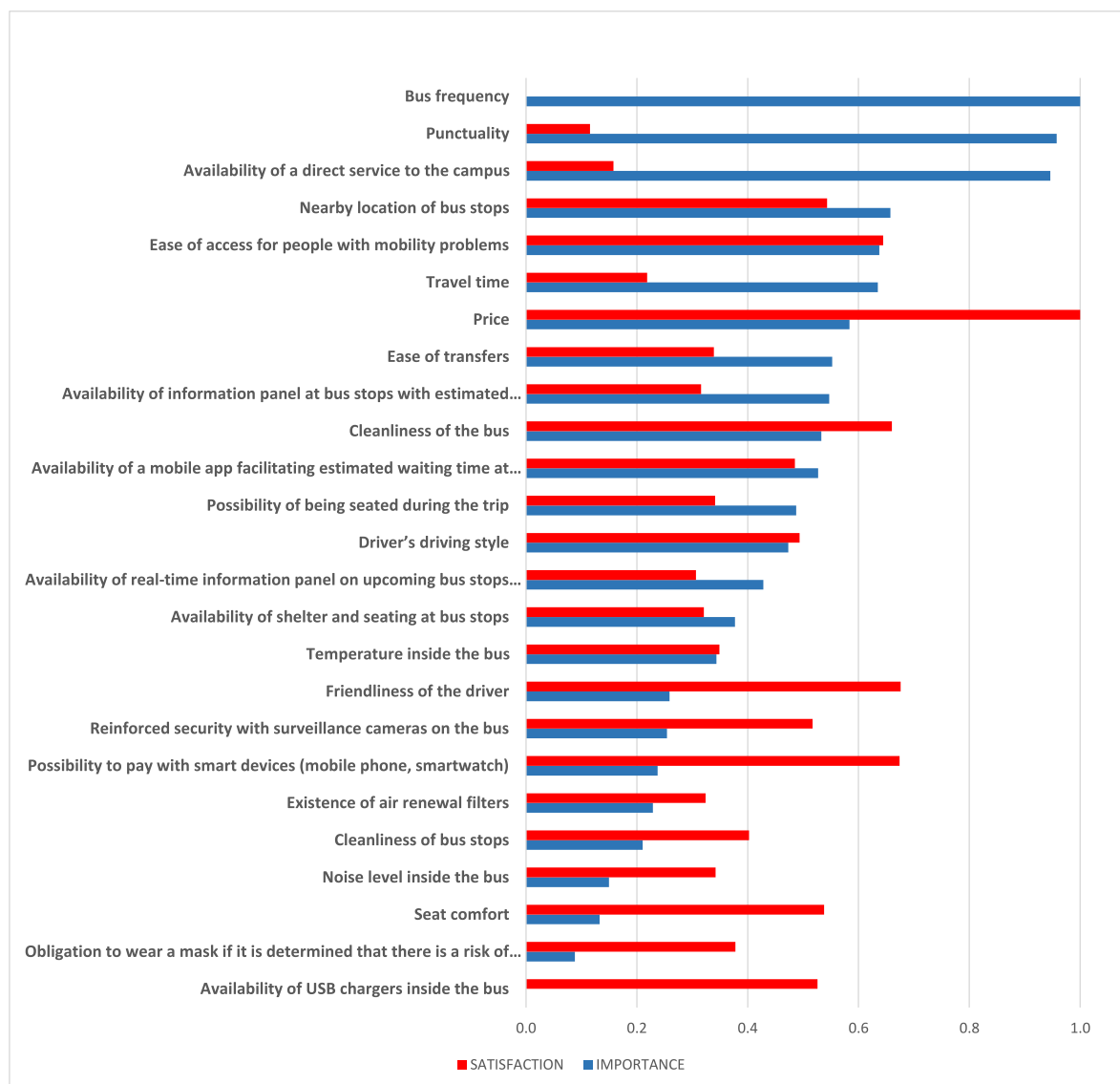


Fig. 4. BWS normalised results.  
Source: Own elaboration.



less satisfied with them than with the reference attribute. By contrast, the rest of the attributes provide a higher level of satisfaction than the reference one.

Finally, the standard deviation of the error component for the importance and satisfaction utilities resulted statistically significant at a 95 % confidence level, confirming the existence of panel correlation among responses of the same individual.

Given that the underlying scales of importance and satisfaction are different; it is not possible to make a direct comparison between the two sets of results unless a transformation is made to convert them to the same scale. As can be seen from estimates in Table 3, the importance scale ranges from  $-0.31$  (item 17) to  $3.22$  (item 3). The remaining items would fall within the aforementioned scale, indicating that a score approaching  $3.22$  would indicate high importance. The same would be true for satisfaction, where the scale now ranges from  $-0.78$  to  $1.29$ . Thus, to facilitate a comparison of the importance and satisfaction results, the estimates were re-scaled to a 0–1 scale using the following formula:

$$\text{Normalized value}_i = \frac{\text{Value of } i - \text{Min}}{\text{Max} - \text{Min}} \quad (7)$$

where *Value of i* is the value of the attribute coefficient obtained from the estimation, *Min* is the lowest value among all the attributes coefficients, and *Max* is the maximum value obtained in the estimation.

The normalised values of each attribute for importance and satisfaction are presented in the graph shown in Fig. 4. The bars in the graph are arranged according to the importance score, allowing for a clear comparison of importance and satisfaction levels for each attribute. Thus, those attributes close to one are considered the most important/satisfying, while those close to 0 are perceived as the least important/satisfying ones. In light of the results, the most important attribute is "Bus frequency", followed by "Punctuality" and "Availability of a direct service to the campus". Meanwhile, the least important ones are "Availability of USB chargers inside the bus", "Obligation to wear a mask if it is determined that there is a risk of contagion", and "Seat comfort".

Analysing the normalised satisfaction results, "Price", "Friendliness of the driver", and "Possibility to pay with smart devices" emerged as the top-rated attributes, generating the highest levels of customer

satisfaction. In contrast, "Bus frequency", "Punctuality", and "Availability of a direct service to the campus" consistently received the lowest satisfaction ratings. It's crucial to note that the study was conducted during a period when a zero-pricing policy was in effect due to the economic crisis. This policy undoubtedly influenced the heightened satisfaction associated with the "Price" attribute.

After transforming the attribute values into relative terms, we can visualise them on a two-dimensional graph to conduct an IPA where the horizontal axis represents the importance of each attribute, while the vertical axis represents the satisfaction level associated with it.

Fig. 5 represents the Importance-Performance Analysis based on the results obtained from the BWS estimation. The numbers represented in the graph are identified as the attributes listed in Table 1. A diagonal line has been introduced to better identify attributes whose level of satisfaction is higher than importance (above the diagonal) and those whose importance is higher than satisfaction (below the diagonal). In addition, the graph is divided into four different quadrants, as in Fig. 2.

According to the IPA model, Quadrant 1 refers to attributes considered very important and producing high levels of satisfaction. The attributes located in this quadrant are "Price" (1), "Cleanliness of the bus" (10), "Ease of access for people with mobility problems" (15) and "Nearby location of bus stops" (22). PT attributes perceived as not very important but with high satisfaction located in Quadrant 2 are "Availability of USB chargers inside the bus" (17), "Seat comfort" (8), "Reinforced security with surveillance cameras on the bus" (9), "Possibility to pay with smart devices" (16) and "Friendliness of the driver" (13). In light of these results, resource misallocation is risky, as the authorities are investing in areas that fail to align with user priorities. In contrast, particular attention should be directed towards the attributes situated in Quadrant 4, as these represent areas of significant importance to users who are currently underperforming. Based on our findings, the attributes that stand out as crucial for enhancing student satisfaction are: "Availability of a mobile app facilitating estimated waiting time at each stop" (20), "Ease of transfers" (5), "Availability of information panel at bus stops with estimated waiting time" (18), "Travel time" (2); and, standing out from the rest, "Availability of a direct service to the campus" (6), "Punctuality" (4) and "Bus frequency" (3). The rest of the attributes are placed in Quadrant 3, indicating a combination of low user

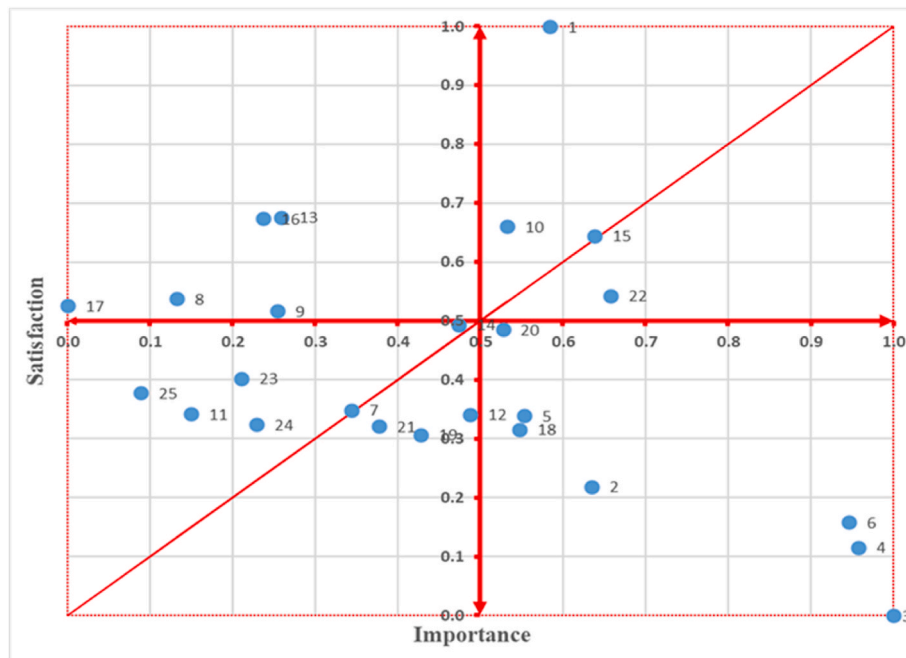


Fig. 5. Importance-Performance Analysis based on BWS results.  
Source: Own elaboration.

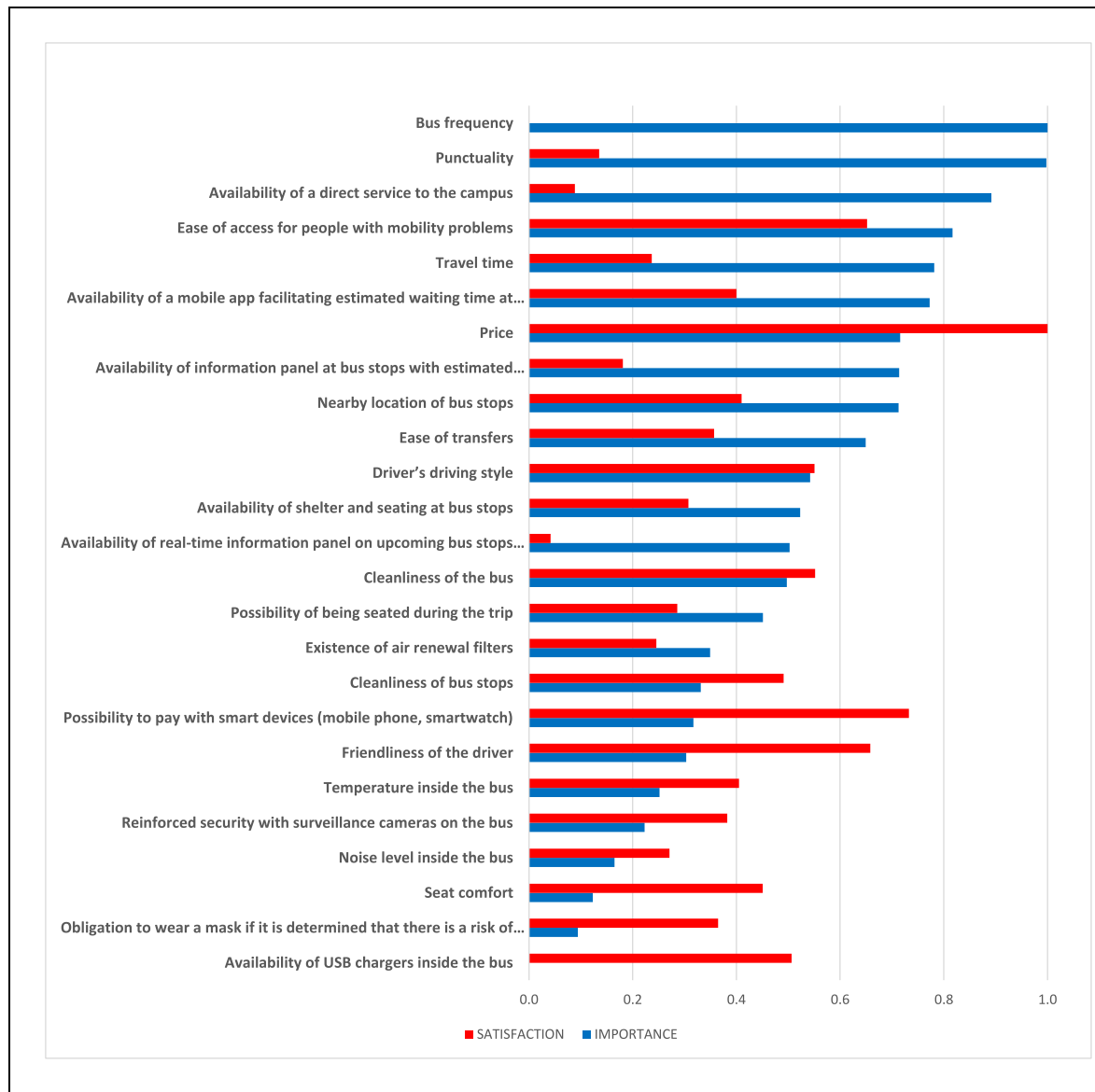


Fig. 6. Semantic scale scores. Normalised results.

Source: Own elaboration.

satisfaction and low perceived importance, making them relatively low-priority areas for improvement.

#### 4.3. Comparing BWS results with semantic scale scores

Respondents were also asked to assess the importance and satisfaction of each attribute using a semantic scale ranging from 1 (least important/satisfied) to 5 (most important/satisfied). The collected data was then normalised in a similar manner to the BWS results. The normalised results are presented in Fig. 6. As in the previous, the bars in the graph are ordered according to the importance score.

As can be observed, both methods yielded remarkably consistent results regarding the top and bottom three ranked attributes for both importance and satisfaction. Thus, in this case, "Bus frequency", "Punctuality", and "Availability of a direct service to the campus" are rated as the most important, while "Availability of USB chargers inside the bus", "Obligation to wear a mask if it is determined that there is a risk of contagion" and "Seat comfort" are perceived as the least important. Slightly different results are obtained for satisfaction with "Price", "Possibility to pay with smart devices", and "Friendliness of the driver"

generating the highest levels of satisfaction; and "Bus frequency", "Availability of real-time information panel on upcoming bus stops within the bus", and "Availability of a direct service to the campus" achieving the lowest levels of satisfaction.

When the entire list of attributes is compared, both methods provide similar overall priority rankings, as indicated by a Spearman correlation index of 0.99 and 0.95 for importance and satisfaction, respectively. However, prioritisation in policymaking extends beyond mere order comparisons. In this sense, the IPA model stands out by incorporating the magnitude of both importance and satisfaction ratings, leading to more comprehensive and informative results.

Fig. 7 illustrates the IPA results derived from semantic scale normalised scores revealing some discrepancies compared to those obtained from BWS. In this case, attributes that before were perceived as very important and generated high satisfaction (Quadrant 1) as "Cleanliness of the bus" (10) and "Nearby location of bus stops" (22) now change to Quadrant 2 ("Possible overkill") and Quadrant 4 ("Concentrate here") respectively; additionally, "Driver's driving style" (14) is now considered as an attribute with high importance and high satisfaction, while in BWS method was considered as a low priority one. Moreover, "Seat comfort"

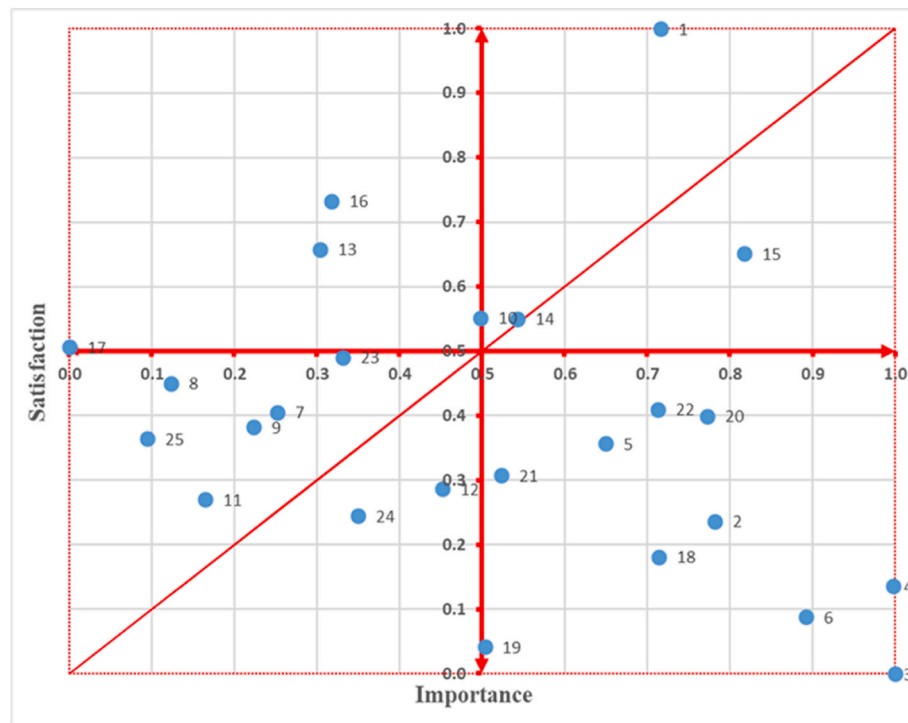


Fig. 7. Importance-Performance Analysis based on semantic scale scores.  
Source: Own elaboration.

(8) and "Reinforced security with surveillance cameras on the bus" (9) now become low-priority attributes, whereas "Availability of real-time information panel on upcoming bus stops within the bus" (19) and "Availability of shelter and seating at bus stops" (21) are, in this case, attributes that should be analysed by the authorities in order to apply policies that change the perception of the users. The rest of the attributes are in the same quadrants for both models.

The diverging IPA results between the two methods suggest different strategies for policymakers to implement. A conflict arises regarding the preferred method for setting policies to improve PT service. Nevertheless, authors such as Cantillo et al. (2021) showed that BWS offers more reliable and more evident results because, in general, respondents tend to overrate the importance and satisfaction of the attributes in the semantic-scale tasks. Other biases, such as central tendency bias due to the subject's avoidance of extreme response choice (Pimentel, 2019), alert using semantic scales to apply policies regarding a list of attributes.

#### 4.4. Discussion

According to the findings, it is recommended that the Mobility Directorate and the PT firms prioritise implementing policies that enhance the frequency of buses, ensure punctuality in keeping services to schedules, and make direct service available to the campus. This will not only improve the overall efficiency of PT but also provide greater convenience and accessibility to students travelling to and from the campus. Therefore, the focus should be on developing and implementing strategies to achieve these objectives while also considering whether maintaining a free-fare policy will be kept in the long run.

The importance of attributes such as bus frequency and service punctuality aligns with the results previously obtained by other authors (Beck & Rose, 2016; de Oña, 2022). These attributes are related to the operational characteristics of the public transportation system, which, in turn, have the greatest impact on the perception of service quality by young adults compared to other age groups (Tavares et al., 2021). Finally, the importance of the attribute related to the availability of direct service to university campuses was also expected. Students are

individuals who, unlike other segments of society, are more likely to avoid transfers (Yen et al., 2017).

Several targeted policies can tackle the identified issues and enhance public transport (PT) service for university students. Dedicated bus lanes emerge as a promising solution to address punctuality. Research by Surprenant-Legault and El-Geneidy (2011) confirms that reserved lanes significantly improve service reliability and on-time performance, both crucial factors for customer satisfaction.

Regarding direct lines to campuses, aligning them with student demand is crucial. Analysing student origins and studying how direct services in their hometowns are operative can provide valuable insights for improvement. This data-driven approach ensures that routes cater to actual needs and preferences, reducing the need for transfers and overall travel time (Sanko, 2020). The main existing problem is that for some municipalities, the density of demand could be very low to establish a direct service. Thus, demand-responsive transport modes such as shared taxis could bring students from dispersed areas to other developed centres where the direct bus routes to campus are already a reality.

Finally, increasing PT frequency is particularly important considering the recent surge in ridership due to free-fare service policies. Subsidies and free-fare PT policies are mainly advocated by the internalisation of many positive externalities that exist in the form of reducing waiting times (González et al., 2015; Mohring, 1972), decreasing land use needs for parking (Cantillo & Ortúzar, 2014; Cruz et al., 2017), providing a more equitable and just access to the university for low-income groups (Irlam & Zuidgeest, 2018), and reducing congestion and transport emissions (Pitsiava-Latinopoulou et al., 2013; Vásquez et al., 2015).

#### 5. Conclusions

The objective of the study was to analyse the level of importance and satisfaction perceived by university students accessing the campuses by PT regarding the main attributes that influence the use of this transport mode, with the main purpose of improving PT matching the service provision with the university students' preferences. A BWS method was

employed to categorise all the attributes according to the IPA quadrants. Results showed that the quadrant “concentrate here” contained three important policy attributes such as “direct service provision to the campus”, “punctuality”, and “frequency”. Thus, it can be recommended that if the University Mobility Directorate and the PT managers want to enhance the PT on the campuses, they should prioritise these three managerial areas.

The results also showed that the overkill quadrant is characterised by the possibility of paying with smart devices and the driver’s friendliness. The first attribute is the consequence of the free-fare policy taken by the Spanish Government to mitigate the effects of the pandemic. However, under normal circumstances, this result might differ as smartphones are becoming popular devices not only to pay TP services but also as real-time information trackers, demand-responsive transport apps and even service quality evaluation tools. Regarding the drivers’ friendliness, it is evident that university students form a particular population segment which, by its youth, values issues differently than old-age segments.

Based on the results obtained, some policies are suggested. Regarding the punctuality of the service, implementing lanes reserved for buses can be a useful initiative to explore. Additionally, increasing the frequency, especially in peak hours and studying direct services from some municipalities in the island that could reinforce the capillarity from low-density areas via demand-responsive transport modes such as shared taxis can change the perception of the individuals with respect to the service. Finally, it is relevant to mention that some resources could be misallocated in the quadrants of “low-priority” and “overkill”, and this policy should also be prioritised to align service quality and satisfaction better. It is necessary to emphasise that by understanding university students’ specific needs and expectations, the authorities and PT operators can tailor service improvements with maximum impact.

It is worth highlighting that while universities may not directly control public transport operations, they can play a crucial role in advocating for student needs. The identified priorities (direct service, punctuality, frequency) can be used by ULPGC to effectively lobby for improved public transport services catering specifically to student commutes. This targeted advocacy, informed by our research, can significantly impact student mobility and satisfaction, even if the university does not directly manage the service itself. This is quite common in most cities worldwide.

The study provides valuable insights for ULPGC to strategically partner with local transportation authorities, aligning service improvements with student preferences. This collaboration can lead to more efficient and student-friendly PT options, directly impacting a critical demographic segment. The study contributes by focusing on a specific student population and outlining actionable steps for ULPGC and PT authorities to improve student mobility through targeted advocacy and collaboration.

Future research on the topic can focus on the importance and satisfaction of the attributes of PT, extending the sample to all users coming to the campuses, i.e. teaching and university services staff. Moreover, other TDM initiatives, such as car-sharing to go to the different campuses located on the island, could be studied to analyse if the students would be willing to choose this transport mode. Regarding active modes, as previously mentioned, the use is not very favourable due to the characteristics of most campuses on the island, except the Humanities campus, whose location in the city centre allows for greater use of such modes. Other interesting TDM initiatives are related to parking restrictions and parking pricing, but these policies are less popular than others among the main stakeholders involved.

We end the conclusions by mentioning three limitations of the study. First, PT was free when the survey was conducted, and it seems evident that this policy might have impacted the level of satisfaction generated by this attribute. Nevertheless, the free-fare policy is becoming quite popular in some universities worldwide (Arif Khan et al., 2023) as the best TDM initiative to increase the number of PT users. Second, importance and satisfaction scales can be very sensitive to future

technological changes, such as dynamic stops or autonomous buses. Recently, one of the two public transport companies in Gran Canaria -SALCAI UTINSA, started an intra-campus service in Tafira using the first autonomous bus that arrived in the Canary Islands. Third, the development of new mobility systems such as mobility as a service (MaaS) or PT on demand, among others, may affect user perception, changing their level of importance and satisfaction concerning the PT alternative.

## CRedit authorship contribution statement

**Javier Hernán Matas-Monroy:** Writing – original draft, Methodology, Formal analysis, Data curation. **Juan Carlos Martín:** Writing – original draft, Methodology, Formal analysis. **Concepción Román:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

- Allen, J., Muñoz, J. C., & Rosell, J. (2019). Effect of a major network reform on bus transit satisfaction. *Transportation Research Part A: Policy and Practice*, 124, 310–333. <https://doi.org/10.1016/j.tra.2019.04.002>
- Arif Khan, M., Patel, R. K., Pamidimukkala, A., Kermanshachi, S., Rosenberger, J. M., Hladik, G., & Foss, A. (2023). Factors that determine a university community’s satisfaction levels with public transit services. *Frontiers in Built Environment*, 9(May), 1–12. <https://doi.org/10.3389/fbuil.2023.1125149>
- Ashraf Javid, M., & Al-Khayyat, M. A. (2021). Factors affecting the student’s intentions to choose carpooling: A case study in Oman. *Journal of the Chinese Institute of Engineers*, 44(4), 332–341.
- Balcombe, R., Mackett, R., Paulley, N., Preston, J., Shires, J., Titheridge, H., Wardman, M., & White, P. (2004). *The demand for public transport: A practical guide. Transportation research laboratory Report TRL593*. London (UK): Transportation Research Laboratory.
- Beck, M. J., & Rose, J. M. (2016). The best of times and the worst of times: A new best-worst measure of attitudes toward public transport experiences. *Transportation Research Part A: Policy and Practice*, 86, 108–123. <https://doi.org/10.1016/j.tra.2016.02.002>
- Bierlaire, M. (2009). *An introduction to BIOGEME 1.8. Transport and mobility laboratory. École Polytechnique Fédérale de Lausanne*. <http://biogeme.epfl.ch>. July, Wardman, M 3.
- Bond, A., & Steiner, R. (2006). Sustainable campus transportation through transit partnership and transportation demand management: A case study from the university of Florida. *Berkeley Planning Journal*, 19(1).
- Brown, J., Hess, D. B., & Shoup, D. (2003). Fare-free public transit at universities: An evaluation. *Journal of Planning Education and Research*, 23(1), 69–82.
- Cantillo, J., Martín, J. C., & Román, C. (2021). A best–worst measure of attitudes toward buying seabream and seabass products: An application to the island of gran Canaria. *Foods*, 10(1), 90.
- Cantillo, V., & Ortúzar, J. D. (2014). Restricting the use of cars by license plate numbers: A misguided urban transport policy. *Dyna*, 81(188), 75–82. <https://doi.org/10.15446/dyna.v81n188.40081>
- Caulfield, B., Browne, S., Mullin, M., Bowman, S., & Kelly, C. (2021). Re-Open our city and campus post-covid: A case study of trinity college Dublin, the university of dublin. *Case Studies on Transport Policy*, 9(2), 616–625. <https://doi.org/10.1016/j.cstp.2021.02.016>
- Cruz, L., Barata, E., Ferreira, J. P., & Freire, F. (2017). Greening transportation and parking at Uni- versity of Coimbra. *International Journal of Sustainability in Higher Education*, 18(1), 23–38. <https://doi.org/10.1108/IJSHE-04-2015-0069>
- de Ona, J. (2022). Service quality, satisfaction and behavioral intentions towards public transport from the point of view of private vehicle users. *Transportation*, 49(1), 237–269.
- de Ona, J., & de Ona, R. (2015). Quality of service in public transport based on customer satisfaction surveys: A review and assessment of methodological approaches. *Transportation Science*, 49(3), 605–622. <https://doi.org/10.1287/trsc.2014.0544>
- de Ona, J., de Ona, R., & Calvo, F. J. (2012). A classification tree approach to identify key factors of transit service quality. *Expert Systems with Applications*, 39(12), 11164–11171. <https://doi.org/10.1016/j.eswa.2012.03.037>
- dell’Olio, L., Cordera, R., Ibeas, A., Barreda, R., Alonso, B., & Moura, J. L. (2019). A methodology based on parking policy to promote sustainable mobility in college campuses. *Transport Policy*, 80, 148–156. <https://doi.org/10.1016/j.tranpol.2018.03.012>
- Echaniz, E., Ho, C. Q., Rodríguez, A., & dell’Olio, L. (2019). Comparing best-worst and ordered logit approaches for user satisfaction in transit services. *Transportation*



- Research Part A: Policy and Practice, 130, 752–769. <https://doi.org/10.1016/j.tra.2019.10.012>
- Esmailpour, J., Aghabayk, K., Abrari Vajari, M., & De Gruyter, C. (2020). Importance – performance analysis (IPA) of bus service attributes: A case study in a developing country. *Transportation Research Part A: Policy and Practice*, 142, 129–150. <https://doi.org/10.1016/j.tra.2020.10.020>
- Esztergár-Kiss, D., & Kerényi, T. (2022). Defining mobility packages by using city specific parameters and user groups: A case study. *Transportation Research Procedia*, 62, 467–474. <https://doi.org/10.1016/j.trpro.2022.02.058>
- Finn, A., & Louviere, J. J. (1992). Determining the appropriate response to evidence of public concern: The case of food safety. *Journal of Public Policy and Marketing*, 11(2), 12–25.
- Flynn, T. N., & Marley, A. J. J. (2014). Best-worst scaling: Theory and methods. In S. Hess, & A. Daly (Eds.), *Handbook of choice modelling*. Cheltenham UK: Edward Elgar.
- González, R. M., Martínez-Budría, E., Díaz-Hernández, J. J., & Esquivel, A. (2015). Explanatory factors of distorted perceptions of travel time in tram. *Transportation Research Part F: Traffic Psychology and Behaviour*, 30, 107–114. <https://doi.org/10.1016/j.trf.2015.02.006>
- Gössling, S. (2017). ICT and transport behavior: A conceptual review. *International Journal of Sustainable Transportation*, 12(3), 153–164. <https://doi.org/10.1080/15568318.2017.1338318>
- Grisé, E., & El-Geneidy, A. (2017). Evaluating the relationship between socially (dis) advantaged neighbourhoods and customer satisfaction of bus service in London, U.K. *Journal of Transport Geography*, 58, 166–175. <https://doi.org/10.1016/j.jtrangeo.2016.11.016>
- Grzybowska, H., Hickson, R. I., Bhandari, B., Cai, C., Towke, M., Itzstein, B., ... Paini, D. (2022). Safe transport: Wearing face masks significantly reduces the spread of COVID-19 on trains. *BMC Infectious Diseases*, 22(1), 694.
- Hamad, K., Htun, P. T. T., & Obaid, L. (2021). Characterization of travel behavior at a university campus: A case study of sharjah university city, uae. *Transportation Research Interdisciplinary Perspectives*, 12, Article 100488.
- Irlam, J. H., & Zuidgeest, M. (2018). Barriers to cycling mobility in a low-income community in cape town: A best-worst scaling approach. *Case Studies on Transport Policy*, 6(4), 815–823. <https://doi.org/10.1016/j.cstp.2018.10.003>
- Jen, W., Tu, R., & Lu, T. (2011). Managing passenger behavioral intention: An integrated framework for service quality, satisfaction, perceived value, and switching barriers. *Transportation*, 38, 321–342.
- Ku, D., Yeon, C., Lee, S., Lee, K., Hwang, K., Li, Y. C., & Wong, S. C. (2021). Safe traveling in public transport amid COVID-19. *Science Advances*, 7(43), eabg3691.
- Lancsar, E., Louviere, J., Donaldson, C., Currie, G., & Burgess, L. (2013). Best worst discrete choice experiments in health: Methods and an application. *Social Science & Medicine*, 76, 74–82.
- Liu, C., Bardaka, E., & Paschalidis, E. (2023). Sustainable transport choices in public transit access: Travel behavior differences between university students and other young adults. *International Journal of Sustainable Transportation*, 17(6), 679–695.
- Logan, K. G., Nelson, J. D., Osbeck, C., Chapman, J. D., & Hastings, A. (2020). The application of travel demand management initiatives within a university setting. *Case Studies on Transport Policy*, 8(4), 1426–1439. <https://doi.org/10.1016/j.cstp.2020.10.007>
- Louviere, J. J., Flynn, T. N., & Marley, A. A. J. (2015). *Best-worst scaling: Theory, methods and applications*. Cambridge University Press.
- Louviere, J., Lings, I., Islam, T., Gudergan, S., & Flynn, T. (2013). An introduction to the application of (case 1) best–worst scaling in marketing research. *International Journal of Research in Marketing*, 30(3), 292–303.
- Louviere, J. J., & Woodworth, G. G. (1990). *Best worst scaling: A model for largest difference judgments, working paper*. Edmonton: University of Alberta.
- Martilla, J. A., & James, J. C. (1977). Importance-performance analysis. *Journal of Marketing*, 41(1), 77–79.
- Matyas, M., & Kamargianni, M. (2021). Investigating heterogeneity in preferences for Mobility-as-a-Service plans through a latent class choice model. *Travel Behaviour and Society*, 23, 143–156. <https://doi.org/10.1016/j.tbs.2020.12.002>
- McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics*. New York: Academic Press.
- Mohammed, A. M., Ukai, T., & Hall, M. W. (2022). University campuses' role in accelerating the natural urban transformation process. *Bulletin of Geography. Socio-Economic Series*, 58, 75–96.
- Mohring, H. (1972). Optimization and scale economies in urban bus transportation. *The American Economic Review*, 62(4), 591–604.
- Mulley, C., Clifton, G. T., Balbontin, C., & Ma, L. (2017). Information for travelling: Awareness and usage of the various sources of information available to public transport users in NSW. *Transportation Research Part A: Policy and Practice*, 101, 111–132. <https://doi.org/10.1016/j.tra.2017.05.007>
- Mulley, C., & Reedy, L. (2016). Travel demand management options for the sydney CBD. *A literature review. Institute of transport and logistics studies*. University of Sydney Business School.
- Myftiu, J., Gigliarano, C., Maggi, E., & Scagni, A. (2024). University commuting during the COVID-19 pandemic: Changes in travel behaviour and mode preferences. *Research in Transportation Business & Management*, 53, Article 101091.
- Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing*, 49(4), 41–50.
- Pérez-Neira, D., Rodríguez-Fernández, M. P., & Hidalgo-González, C. (2020). The greenhouse gas mitigation potential of university commuting: A case study of the university of león (Spain). *Journal of Transport Geography*, 82, Article 102550.
- Pimentel, J. L. (2019). Some biases in Likert scaling usage and its correction. Article in *International Journal of Sciences: Basic and Applied Research*, 45(1), 183–191. <http://gssrr.org/index.php?journal=JournalOfBasicAndApplied>.
- Pitsiava-Latinopoulou, M., Basbas, S., & Gavanis, N. (2013). Implementation of alternative trans- port networks in university campuses: The case of the Aristotle University of Thessaloniki, Greece. *International Journal of Sustainability in Higher Education*, 14(3), Article 310323. <https://doi.org/10.1108/IJSHE-12-2011-0084>
- Potoglou, D., Burge, P., Flynn, T., Netten, A., Malley, J., Forder, J., & Brazier, J. E. (2011). Best-worst scaling vs. discrete choice experiments: An empirical comparison using social care data. *Social Science & Medicine*, 72(10), 1717–1727. <https://doi.org/10.1016/j.socscimed.2011.03.027>
- R Core Team. (2013). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. URL <http://www.R-project.org/>.
- Ribeiro, P. J., & Fonseca, F. (2022). Students' home-university commuting patterns: A shift towards more sustainable modes of transport. *Case studies on transport policy*, 10(2), 954–964.
- Ribeiro, P., Fonseca, F., & Meireles, T. (2020). Sustainable mobility patterns to university campuses: Evaluation and constraints. *Case Studies on Transport Policy*, 8(2), 639–647. <https://doi.org/10.1016/j.cstp.2020.02.005>
- Romanowska, A., Okraszewska, R., & Jamroz, K. (2019). A study of transport behaviour of academic communities. *Sustainability*, 11(13), 3519.
- Rotaris, L., & Danielis, R. (2015). Commuting to college: The effectiveness and social efficiency of transportation demand management policies. *Transport Policy*, 44, 158–168.
- Rotaris, L., Danielis, R., & Maltese, I. (2019). Carsharing use by college students: The case of Milan and Rome. *Transportation Research Part A: Policy and Practice*, 120, 239–251. <https://doi.org/10.1016/j.tra.2018.12.017>
- Sanko, N. (2020). Activity-end access/egress modal choices between stations and campuses located on a hillside. *Research in Transportation Economics*, 83. <https://doi.org/10.1016/j.retrec.2020.100931>
- Surprenant-Legault, J., & El-Geneidy, A. M. (2011). Introduction of reserved bus lane: Impact on bus running time and on-time performance. *Transportation Research Record*, 2218(1), 10–18.
- Tavares, V. B., Lucchesi, S. T., Larranaga, A. M., & Cybis, H. B. B. (2021). Influence of public transport quality attributes on user satisfaction of different age cohorts. *Case Studies on Transport Policy*, 9(3), 1042–1050. <https://doi.org/10.1016/j.cstp.2021.04.018>
- Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.
- ULPGC. (2022). *Estudio de movilidad de la comunidad educativa de la Universidad de Las Palmas de Gran Canaria (ULPGC). Las Palmas de Gran Canaria (Spain): Técnicos en Socioanálisis*.
- Vásquez, L., Iriarte, A., Almeida, M., & Villalobos, P. (2015). Evaluation of greenhouse gas emissions and proposals for their reduction at a university campus in Chile. *Journal of Cleaner Production*, 108, 924–930. <https://doi.org/10.1016/j.jclepro.2015.06.073>
- Vuchic, V. R. (2017). *Urban transit: Operations, planning, and economics*. Hoboken (NJ): John Wiley & Sons.
- Yen, B. T. H., Tseng, W. C., Mulley, C., Chiou, Y. C., & Burke, M. (2017). Assessing interchange effects in public transport: A case study of south east queensland, Australia. *Transportation Research Procedia*, 25, 4019–4037. <https://doi.org/10.1016/j.trpro.2017.05.268>