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Time slot choice analysis for Demand-Responsive Transport service: evidence from Ragusa province, Italy

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Abstract:

The transition to sustainable mobility requires the implementation of strategies that make the sector more environmentally friendly and efficient. In recent years, we have witnessed a transition phase, i.e. the implementation of policies and actions that reduce the use of private vehicles (especially those with combustion engines) and promote greener modes of transport such as public transport, cycling, walking and innovative, climate-friendly mobility solutions. It is therefore possible to implement a series of improvement measures and strategies (e.g. innovative tariffs, service quality, complementary services and greater efficiency, as well as the transition to green fleets). It is also essential to implement complementary transport services such as on-demand or shared. This research study analyses connections in the province of Ragusa—where a Demand Responsive Transport service (DRTs) operates—using a hub and spoke model to discretise travel patterns. This research analyses the aspects related to the time slots in which the service is used using a modelling linked to the Random Utility Models (RUMs) and through the definition of a binomial logit model (BNL). The choice of RUM enables identifying relationship between the chosen alternative and the individual decision. The calibrated model reveals that the most influential attribute in the choice of the time slot, for the service analysed, is the area of origin. This highlights how users choose the time slot mainly based on the area of origin, which, given the characteristics of the service, corresponds to the direction of travel; among other attributes tested, the availability of buses was found to be significant. The results are meaningful for improving the existing services and for defining a complementary service of local public transport and on-demand services. Furthermore, the proposed framework can be extended to other aspects of the decision process involved in DRT adoption.

Keywords: *flexible and complementary mobility, DRT time slot, random utility model, binomial logit model, Ragusa case study*

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1. Introduction

Sustainable transport is a key element in achieving the sustainable development goals of Agenda 2030, in particular Goal 11 (sustainable cities and communities) and Goal 13 (climate action). TheAgenda 2030 aims to ensure access to an affordable and sustainable transport system for all, reducing emissions and improving air quality (Rodrìguez et al, 2023; Chn, 2021).
Several studies in the literature promote walking as the most sustainable form of transport, but this is not possible to apply for medium or long distances (over 1 km) and if there are critical issues in terms of weather, climate or geomorphology (such as steep slopes) (D'orso et al, 2025; van der Vlugt, 2025).
It is clear that a specific transport system needs to be planned that can guarantee that everyone can move as the areas and reasons for moving vary (Ureta, 2008; Walker, 2024)
The evolution of the transport supply (services and infrastructure) aims to mitigate the effects on the environment by reducing the use of the private vehicle and spreading green transport services, such as electric vehicles or public transport. (Barakat et al, 2024; Lättman and Otsuka, 2024).
The evolution of multimodality in transport indicates the increasing integration of different transport modes (such as trains, trucks, ships, planes and/or bus) to optimise the movement of goods and people. This approach aims to reduce costs, improve efficiency, increase flexibility and reduce environmental impact.
This can be pursued by increasing the deployment of digital platforms (MaaS) (El Mustapha, 2024) but also by offering improved public transport services, ensuring greater punctuality and flexibility (Sörensen et al, 2021; Meyer et al, 2025; Sviridova et al, 2025; Baier et al, 2024).
Several studies over the years have adopted different methodologies to analyse public transport services such as multi-criteria analysis (i.e. MCDA/MCDM) (KICINSKI and Solecka, 2018) or analytic hierarchy process (AHP) or fuzzy Analytic Hierarchy Process (FAHP) (Solanki and Agarwal, 2024) and some of them propose integration with other modal forms.
DRT is a form of transport that has gained popularity in recent years and is expected to grow in the years to come (Campisi et al, 2021; Wang et al, 2023).
If properly implemented, communicated to users and integrated with traditional fixed-line services, DRT has the potential to shape the mobility of the future.
However, DRT projects are often designed and implemented without proposing integration between the public transport system and DRT (Cebecauer et al, 2021).
While the creation of separate systems may seem at first glance to be the easiest way to implement such a paradigm, a very high cost emerges later, which is often overlooked.
Unfortunately, many of the DRTs implemented over the last two decades around the world have failed because they did not consider the type or size of the DRT system in relation to the target market (Jevinger & Svensson, 2024).
There is no doubt that the choice depends on the type of user and therefore on age, income, gender and external factors.
To achieve the goal of optimising public and shared transport and making people free to move, it is essential that DRT be fully integrated with other scheduled transport services.
There is no doubt that these goals must be respected and pursued not only by service users but also by operators and public administrations where they are implemented:

– public administration and transport operators who neglect this aspect are then faced with several critical issues.
– Users will inevitably need to use multiple separate apps, one for DRT, another for public transport, and potentially, additional ones for shared mobility and micro-mobility are also considered.

This situation creates significant confusion and results in a poor user experience, which goes against the mission of making life easier for all travellers. Consequently, travellers may lose confidence by entering a vicious circle that will ultimately hinder adoption of DRT and intermodality.
In this situation, in-vehicle hardware and software solutions will be unnecessarily duplicated, with huge additional costs due mainly to installation and maintenance.
Drivers will have to manage multiple systems, making their daily tasks increasingly daily tasks increasingly cumbersome, generating dissatisfaction on several levels.

The management staff of transport operators will continue to find it difficult to effectively manage day-to-day operations and successfully govern the overall mobility scenario for their organisation.

Due to the lack of a centralised tool for the management of both Local Public transport (LPT)and DRT, their operational flexibility will therefore be greatly reduced (Campisi et al, 2022; Baier et al, 2021).

Public administrations that subsidise the mobility ecosystem with taxpayers' money will suffer from the duplication of unnecessary costs to support both public transport and potentially unnecessary DRT and vice versa (i.e a use of individual and/or unconnected apps that would lead to the user being unaware of the various travel options).

The full integration of DRT and LPT services , introducing shared mobility and micro-mobility where possible, avoids unjustified cost increases, facilitates the operation of administrative staff and improves the user experience by exploiting the inherent ability of demand responsive mobility to act as a feeder service of the transport network (Franco et al, 2020; Melo et al, 2024).

Effective intermodality enables MaaS (Mobility-as-a-Service) on a large scale, which aims at adapting mobility to the needs of passengers to provide freedom of movement, while rationalising the mobility scenario in a holistic manner, this approach is cornerstone of today's mobility and the goal for the future transport (Del Ponte et al, 2022; El Mustaoha et al, 2024; Ho & Tirachini, 2024).

MaaS integrates different transport services into a single digital platform that supports journey planning, booking and payment.

This system allows users to easily switch between transport modes, benefiting from flexible and demand-driven pricing (Campisi et al, 2021).

It enables a barrier-free, user-centred mobility experience by treating transport as a holistic service.

Studies show that although prices and fare structures play a role, the actual use of public transport is mainly determined by the quality and availability of the service.

Key factors include:

– Frequency and reliability: high service frequency and punctuality significantly increase attractiveness (Alonso-González et al, 2020).
– Service availability: extended service improves accessibility and reduces travel distances (Li & Voege, 2017).
– Comfort and safety: modern vehicles, which prevent crowding in vehicles and stations, and clean and safe transfer infrastructures are crucial to the passenger experience (Muller et al, 2021).
– Intermodally: Seamless integration with other modes of transport, such as car sharing, bicycles and on-demand services, improves flexibility and convenience (Stopka et al, 2018).

The design of public and shared mobility solutions cannot be the result of a top-down decision but rather must follow a bottom-up approach that starts from the needs of the people who will use the services.

These needs are dynamic and evolving over time and changing between users. The integration of different transport schemes makes it possible to address real scenarios and offer solutions tailored to individual users' needs, by addressing the problem first, rather than starting from a predetermined solution.

Flexibility also means being open to third-party systems: being able to integrate DRT into a broader mobility scenario is the key to implementing a future-ready system where people are truly free to move around and could do so in an economically and environmentally sustainable way (Sörensen et al, 2021; Baier et al, 2024).

Punctuality is a crucial aspect in ensuring user satisfaction and system efficiency (Kim et al., 2025).

DRT is great when it comes to serving areas with low and unconcentrated demand but may not be the best choice in other areas or when demand is growing rapidly.

Having a single software platform allows seamless switching from one paradigm to another, enabling interoperability and saving costs.

Some of the above factors can be more easily achieved by considering transport modes complementary to LPT, such as the DRT defined in this research.

Many of the critical issues encountered in DRT services arise from the study of demand; since they are primarily aimed at residual demand flows, the aggregate models typically proposed in the literature, calibrated for mass services, may not be appropriate. The DRT literature has highlighted the importance of studying socio-demographic attributes, while contributions based on flow analysis are fewer, and the issue of time slots is less studied. These limitations are likely also linked to the heterogeneity of

DRTs The advantage of flow-based models is their relative ease of replication; furthermore, they do not require the design of complex questionnaires but can be created starting from available data from transport operators.

The aim of the research is twofold:

- To propose a methodology for determining the probability of choosing a time slot, for a DRTs with the characteristics described. Reference is made to a service operating between a main hub and several peripheral areas.
- To apply the proposed methodology to a case study, to verify which variables most influence the choice of time slot.

The paper is structured as follows: Section 2 highlights the factors that can influence the planning and optimisation of public transport services and focuses on the aspects that can improve the combination of LPT-DRT. Furthermore, the potential of DRT in low-demand areas to improve sustainable mobility, ensure flexible and punctual services and, above all, improve social inclusion is briefly examined. In Section 3, a hub and spoke analysis methodology is defined that can consider the trips to/from potential attractor nodes, including small villages, analysing an implemented DRT.

Furthermore, in this paper, the basic formulation of a Multinomial Logit model (MNL) for calculating the probability of choosing a DRT in the examined area is considered.

In section 4, the calibration of the model and the related results are defined and relative results discussion and finally in section 5 there are the conclusions.

2. Background and Literature review

The development of urban planning and mobility includes various strategies and actions to increase the concept of sustainability starting with the promotion of walkability (Campisi et al, 2020; Garau et al, 2024). This is feasible for short distances instead there is a tendency to promote multimodality or the use of collective transport for medium and long-distance travel (Pfoser, 2022).

There is no doubt that complementarity and multimodality enable the user to reduce the likelihood of using a private vehicle (Rayaprolu and Levinson, 2024).

Public transport services must be rethought and optimised to meet the changing needs of passengers (Parbo et al, 2014).

Several factors play a crucial role and characterise both the process of strategic planning of the network and its efficient configuration but also the fleet scheduling and the development of a competitive fare system (Gkiotsalitis, 2023).

This process must consider both planning and design and optimisation aspects. This makes it possible to create a solid link between the creation of a sustainable public transport network and aspects of financial sustainability.

Therefore, it is necessary to promote the study and development in the medium to long term actions such as:

- Passenger demand analysis and forecasting (i.e. the analysis of data on passenger numbers, commuter flows, and mobility models enables accurate forecasting of demand and forms the basis for demand-based service planning) (Rahmani et al, 2025).
- Development of the public transport network, (i.e. the planning and optimisation of routes, intervals and transfers improve accessibility and ensure an efficient public transport service.) (Xiao et al, 2024)
- Design of an attractive fare system (i.e. co-ordinated fare structures, digital ticketing solutions and fair pricing models encourage the use of public transport and improve accessibility for all passengers) (Lin et al, 2021).
- Infrastructure planning and investment, (i.e. the expansion and modernisation of bus stops, depots and vehicle fleets ensure the efficiency of public transport and contribute to its long-term attractiveness) (He et al, 2022).

Furthermore, close coordination with municipal urban planning is essential to optimally integrate public transport into other mobility concepts. In particular, the integration with other transport modes and the promotion of new mobility solutions plays a significant role.

Several iterative steps must be followed, which are essential for an efficient transport system or must consider. By applying scientific methods, transport planners can gain sound insights into current and future demand patterns, enabling them to optimise public transport planning with greater precision and certainty.

Based on the demand analysis, the public transport service is systematically improved. Accessibility, immediacy, travel times, punctuality and reliability are key factors that determine the quality-of-service planning (Kramarz and Przybylska, 2021; Kuziev et al. 2023).

A well-designed network ensures that connections are easily accessible and efficient. It forms the basis for planning and directly influences subsequent vehicle and shift planning. Mistakes made in this initial phase impact the entire operation, affecting both operating costs and passenger satisfaction. Systematic planning of public transport with services such as DRT can fulfil the above mentioned (Kim, 2020; Tsigdinos et al, 2024).

Road layout changes, new speed limits, and ongoing or planned construction projects have a significant impact on timetable planning. Construction work or diversions may result in longer travel times. (Bérczi et al, 2017; Wang et al, 2021).

Therefore, infrastructure-related disruptions should be considered early in the planning process to adapt route alignments and service frequencies as needed, minimising delays and maintaining operational reliability. Finally, planning timetable is a complex process that considers operational, infrastructure and demand factors. This approach aims is to create a reliable, efficient and cost-effective public transport service that meets both operational requirements and passenger needs. (Cede, 2002). These aspects will have to be given greater attention in the case of complementary and more flexible services such as the LPT-DRT combination.

2.1. The development of DRT transport mode in weak demand areas

DRT services are a flexible, user-centric transportation mode that allows passengers to specify their desired pick-up and drop-off locations and times. (**Tejero-Beteta et al, 2024; Schasché et al, 2022**). While not operating on fixed routes or schedules like traditional public transport, DRT services incorporate the concept of time slots or time windows to manage reservations and coordinate vehicle routes.

The operating hours of DRTs vary greatly by region and operator. In some cases, the service may also be active on holidays and at night (Logan, 2007). Some services operate from Monday to Saturday. Other services may be active during the morning and late morning and in the afternoon. Some services may also be active throughout the day or even late into the night. On Saturdays and holidays, some services may also be active on these days. Other services may be active with limited hours and during some periods with higher demand, such as the Christmas holidays, the service may be intensified at certain times.

DRTs show a great variability; this allows the DRT system to efficiently group multiple requests into a single route and schedule, optimising the use of resources (Campisi et al, 2022).

Timetable planning must be demand-oriented, i.e. adapt to the needs of travellers. This approach helps to minimise environmental impact and operating costs while ensuring a high quality with waiting and travel times kept to a minimum.

In general, timetable planning must comply with current regulations and industry rules, for example those relating to work shifts. Collaboration between public transport operators, local authorities and travellers is therefore important to ensure a quality service. In the case of a complementary LPT-DRTs , greater flexibility must be guaranteed by analysing the time slot choices made by users to improve services. To optimise a DRT and therefore its complementarity to the LPT, the following aspects must be considered:

– Flexibility and customisation, (i.e. considering aspects such as origin and destination as the service must allow the booking of journeys with customised departure and destination, anywhere in the served area, and aspects such as timetables as the user must be able to choose the most convenient departure time, without being bound to fixed timetables.)
– Reservation methods, (i.e. the possibility of being able to book via a specific mobile application (which can exemplify booking, payment and trip management) and/or via telephone useful for less digital users or for special situations.)
– Route efficiency (i.e. the definition of optimisation algorithms to optimise vehicle routes, minimising waiting times and fuel consumption but also the study of reachability as the area served and the frequency of vehicle passage must guarantee good reachability for users.)Particular attention must be paid to the study of costs and tariffs, considering the possible implementation of fixed or variable tariffs based on distance, rush hour and other factors;

the analysis of operating costs (vehicle maintenance, personnel, etc.) is essential for assessing the sustainability of the service.

- Intermodality as the on-demand service can effectively complement public transport timetables by offering intermodal solutions to connect peripheral or low-demand areas.
- Co-ordination as co-operation between different transport companies, both public and private, can improve the efficiency of the mobility system.
- Finally, it is necessary to consider the type of service to be implemented, namely:
- Fixed line with reservation: transport lines with defined routes, but with trips made only if there are reservations.
- Fixed line with deviations: lines with defined routes, but with the possibility of small deviations to reach the users' stops.
- "Many to one" model picks up passengers at different points and takes them to the same destination.
- "Many to many" model offers maximum flexibility, with the possibility of booking trips between any starting point and destination.

It should also be noted that these services are usually booked through apps, websites or phone calls, allowing passengers to specify the desired location and time. Once a passenger books a trip with a time slot, the DRT system analyses the request and combines it with other similar requests to optimise the vehicle's route and schedules.

Unlike fixed-route public transport, DRT can adjust their routes and schedules in real time to accommodate new bookings or changes in demand. DRT services can include “dial-a-ride” services, where users book rides via phone or app, and dynamic apps that adjust routes in real time based on demand.

In literature, mobility demand models for users usually assume that the reasons for travel are known and, at the same time, they are calibrated and applied in each time slot (Cascetta, 2013).

Studies start from the time of the peak demand on the network; for example, for the reason of the home-school trip, the morning time slot is considered.

The methodology described is derived from the need to assess the impact of mobility, in this case school, during peak hours.

DRTs, due to their characteristics, can instead present a variable trend in demand, precisely because they must serve quantitatively lower mobility flows than those of peak hours.

These services are designed in a way often linked to low demand; the methodological premise is often different; the problem to be analysed is the identification of the time at which users will move. Because of their flexibility, the peak time of these services must often be determined downstream of quantitative evaluations and not upstream.

For dedicated DRTs (i.e. services that connect urban areas with modal interchange points such as airports or railway stations) the reasons for the movement can be defined before the analysis; in the case of non-dedicated DRT, such as a large part of the services linked to urban mobility, these reasons can only be considered. This aspect translates into having to consider the reference time slot as a variable to be studied and not as input data.

2.2. The development of DRT in Italy

Addressing the lack of access to transport for people living in peri-urban areas presents a major transport challenge, not only due to equity concerns, but also because their dependence on the car threatens urban transport provision (Thao et al, 2023).

One of the tools suggested for network improvement (with the potential to develop cost-effective services) has been dial-up buses.

Most of the bus improvement plans and enhanced partnerships do indeed rely, at least in part, on dial-up bus services.

However, to date, Italy’s experience with dynamic dial-up transport has been “uneven” to say the least. Experimental services have been enthusiastically launched and then quietly withdrawn (with the occasional implosion). While “matching demand to vehicles” seems like a non-trivial efficiency idea, the reality of doing so within an already limited bus network has not delivered fantastic returns.

Now the situation in Italy is rather fragmented: in fact, if on the one hand there are complex cities in which transport has a heavy impact on air pollution, in some local areas sustainable mobility projects have achieved surprising results. This is the case of Milan, where the implementation of SUMPs (Sustainable Urban Mobility Plans) is helping the city administration to reduce harmful emissions.

The strategy of the Lombard metropolis includes a focus on the Mobility as a Service model, offering inhabitants integrated solutions for shared mobility with flexible transport systems, car, bike, scooter and e-bike sharing. Furthermore, the strengthening of the cycle network and low-emission public transport are planned, interventions that have positioned Milan in sixth place in the world for green mobility among large cities (Annunziata et al, 2022). Obviously sustainable urban mobility is promoted by the European Union, as 25% of pollution on the continent is due to road transport. The focus of the European institutions is therefore the strengthening of the public transport service, the implementation of sharing mobility and the use of new digital technologies to improve the efficiency of travel (*Eaa Europa*).

In addition to a greater commitment to environmental issues, Italy is a very complex territory where sparsely populated areas host almost 40% of the Italian population (Bellini et al, 2003; Pavanini, 2023; Kercuku et al, 2023).

These territories present real critical issues in mobility, even in the most banal of daily movements. In these areas, going shopping, going to the doctor or the hairdresser requires the organisation of a real structured journey. The car is often the only means of transport available.

Low density, complex roads, large distances in peri-urban and rural areas make public service with traditional means of transport particularly difficult (Cattivelli et al, 2021; Gottero et al, 2023). In fact, in most cases, these areas are characterised by inadequate public transport coverage. Yet the right to transport applies everywhere, even to the most remote areas. It remains difficult for transport authorities to fulfil their obligations.

The peri-urban and rural area appears to be a privileged area for the development of on-demand transport (Qiao & Yeh, 2023; Thao et al, 2023; Vasconcelos et al, 2025). Its flexibility in terms of operation and speed of implementation, allow it to adapt to the constraints of these spaces, all at a cost accessible to small communities.

2.3. The use of logit models in analysis of DRT use

The use of logit models for the design and analysis of DRT services is starting to spread in the literature. Now, however, there are not many contributions. In this context, it is considered useful to refer to logit models for their behavioural implications, as will be discussed in Section 3.

In the following, the contributions related to application of logit models to DRT-related problems are presented.

Study by (Ryley et al, 2014) distributed a survey to determine the propensity to use DRT from the general population, in the urban area of Rochdale in Greater Manchester and the rural district of Melton Mowbray in Leicestershire. The authors proposed a Random Parameters Logit for the analysis of bus vs. DRT and car vs. DRT choices; the choices are traced back to attributes of travel time and travel cost and, in the case of the bus, to the walking travel time to the stop. The work does not refer to a specific service, but defines different market niches, in particular identifying solid markets from emerging ones. "Rural hoppers and general public" are indicated as one of the most solid market segments for DRT.

Ordered logit model proposed by (Wang et al, 2015) analysed the propensity of users to use a DRT service operating in the largely rural Lincolnshire area. The model used propensity as the dependent variable, expressed as the frequency of use of the service. DRT are used more to travel for work, by disabled and more rural residents. Service is not specified for a certain segment of the population, and no statistical considerations are made on timetables.

The model proposed by (Dong et al, 2022) in the context of the Dial-A-Ride Problem (DARP) captures users' preferences in a DRT context from a strategic planning aspect; In the context of the proposed Mix Integer Linea Programming model, they model users' utilities considering various alternatives, including DRT, through a MNL. They insert class-based attributes into the utility based on different socio-economic factors.

(Hussain et al, 2023) analysed the willingness to use DRT in Karachi, Pakistan. A multinomial logit and a nested logit were proposed, considering two groups of users: students and working class. Several independent variables impact the use of DRT, both sociodemographic (e.g. Gender, Income, Age, Occupation) and specific to the alternatives (e.g. Travel time and cost).

Study of (Tordai et al, 2024) conducted a stated preference (SP) survey about potential users' preferences towards demand responsive transport at a rural Eastern European town in Hungary. The calibrated

multinomial logit model estimates the potential user preference, considering different attributes of the alternative (such as travel time or service cost).
Model proposed by (Park et al, 2025) explores the concept of M-DRT (Demand responsive transit for Metropolitan area); the proposed models analyse the attitudinal characteristics of individuals in modal choice in the metropolitan area of Seoul. The model considers some psychological constructs (car-oriented, positive perception on M-DRT, and satisfaction) as potentially impactful; at the same time some attributes of the alternative, such as travel time.
A research conducted by (Caramuta et al, 2025) calibrated two binomial logit models for the design of a DRT for students at the University of Trieste. The calibrated logit models highlight how the propensity to use DRT with respect to the users considered depends mainly on the destination, the chosen time slot, the day of the week. In the second proposed model, some time slots are independent variables of the model.
The analysis conducted was carried out during the design phase of the service. The contributions in literature highlight that logit models have widespread and consolidated applications; however, most of the analyses conducted concern the study of the propensity to use DRT compared to other alternatives, hypothesising links with various sociodemographic and territorial attributes. This study intends to fit into this line of research, considering the study of time slots as a choice alternative, an element not widespread in literature.
Many of the contributions considered include references to users' sociodemographic characteristics and their propensity to use them. Less common in the literature are analyses related to on-demand services that focus on flow studies; these are common in the literature on transport system planning (Cascetta & Nguyen, 1988; Marzano et al., 2009) and have several advantages: they are easily updated, easily replicable, and do not require the design of specific surveys. This contribution aims to address this gap, highlighting any relationships between the choice of time slots, relationships, and other elements deducible from demand flow surveys (such as seasonality or day of the week) for a DRT service.

3. Methodology

The proposed methodology aims to analytically represent the study of the characteristics of user behaviour starting from the trips made with a DRT. This section describes the methodology adopted in this work. The specific characteristics of the service, with its partially fixed nature, are presented in subsection 3.1. Subsection 3.2 presents the methodological steps used for the study; for the reference on Random Utility Models, the authors are referring to (Ben-Akiva & Lerman, 1985; Cascetta, 2013; Ben-Akiva et al., 2019).

3.1. Characteristics of the service

The methodology described describes a DRT service with the following characteristics:

– Service operating between zone A_0, main hub of the study area, and zones A_k, with k=1, 2,…, N, that are the peripheral zones to be connected to the main hub with the DRT service.
– Zone A_0 is characterised by $h_{0,1}$, $h_{0,2}$, …, $h_{0,H}$ stops; generic peripheral zone Ai is characterised by M_i stops; generic stop in peripheral zone A_k is m_{kp}, with p=1, 2, …, M_k.
– Service is semi-rigid. Deviations from the route are permitted based on reservations, both at origin and destination.
– Single rides between A_0 and generic A_k are allowed;
– Rides inside A_k or between A_{k^*} and $A_{k^{**}}$, with k*≠k**, are not allowed.

Service scheme is described in Fig. 1.

3.2 - Modeling

To study the choice of time slots refers to the Random Utility Models (RUM) modelling. RUMs are models that allow us to study the choices of the generic user *i* when he must choose from a finite set of alternatives I^i. RUM models allow us to indicate the utility associated with user i and alternative j as:

$$U_j^i = V_j^i + \varepsilon_j^i \qquad (1)$$

Where V_j^i is the systematic component of utility, a function of the characteristics of the alternative and/or the individual, and ε_j^i it is the random residual, which represents the unobservable random component of utility. RUMs offer great flexibility and allow users' choices to be modelled as a function of their own characteristics and the alternative.

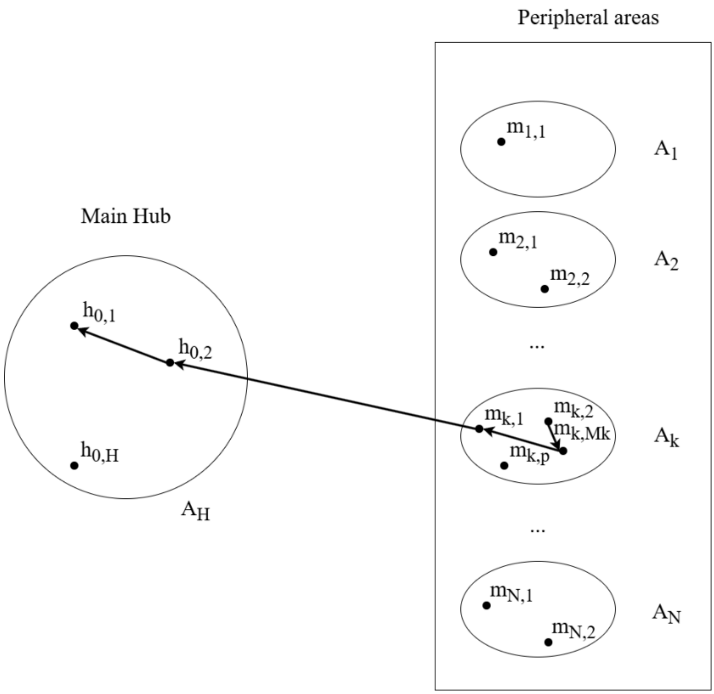

Fig. 1. Example of service scheme operating between the main hub of the study area, and zones A_k. Ride represented is connecting 3 stops in A_i with two stops in A_H.

RUMs differ from each other based on the assumptions made on the structure of the alternatives and on the characteristics of the random residual. V_j^i may have different specification; for reason of analytic convenience, usually it is assumed that V_j^i is a linear function with coefficients of the attributes β_k expressed as

$$V_j^i = \sum_k \beta_k X_{kj}^i \tag{2}$$

In this paper, basic formulation of RUMs is considered, the Multinomial Logit (MNL) model, in which the random component is assumed independent and identically distributed according to a Gumbel random variable with zero mean and θ parameter. MNL models allow to model the choice of generic alternative j in closed form as:

$$p(j) = \frac{e^{V_j/\theta}}{\sum_k e^{V_k/\theta}} \tag{3}$$

The choice of RUMs allows to define a relationship between the chosen alternative and the single individual. The proposed methodology is therefore useful to analyse individual behaviour in a context in which critical time slots and reasons for travel are not known a priori, as in the case of DRT. Un caso particolare di modello logit multinomial in cui sono presenti solo due alternative si definisce modello logit binomiale.

Model calibration consists of estimating the values of the coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ based on the choices made by the users of the sample. The most widely used method is Maximum Likelihood (ML) estimation. It is assumed that a model is better the more it reproduces the observed choices: the greater the probability of observing the sample's behaviour, the greater the model's likelihood.

The likelihood therefore depends both on the structure of the specified model and the type of sampling used. The maximisation of the probability that the model observes the choices adopted by the sample of users is related to the study of the parameters

$(\boldsymbol{\beta},\boldsymbol{\vartheta})_{ML}$. This estimate is obtained by maximising the function

$$(\boldsymbol{\beta},\boldsymbol{\vartheta})_{ML} = \arg\max lnL(\boldsymbol{\beta},\boldsymbol{\theta}) = \arg\max \sum_{i=1,\dots,n} ln\, p^{i}(j(i))(\boldsymbol{X^{i}},\boldsymbol{\beta},\boldsymbol{\theta}) \tag{4}$$

Once the parameter values have been obtained through calibration, it is essential to verify their validity. This can be done using informal and formal tests

Informal tests are based on the expected behaviour of the model rather than on formal statistics. They are called "informal" because the evaluation of the parameters does not involve computing a specific statistic or indicator but is carried out by checking whether the parameter values are consistent with expectations. A typical aspect that is considered in informal validation is the sign of the parameter. For instance, attributes such as travel time or cost are expected to have negative coefficients because an increase in these attributes should decrease user utility. If this is not the case, it may indicate that, during model specification, some additional attributes that "balance" time and cost effects were omitted.

Formal tests on individual coefficients are based on specific statistical indicators computed from the maximum likelihood estimates $(\beta,\vartheta)_{ML}$. A commonly used test in discrete choice modelling (Cascetta, 2013) is the t-test on individual coefficients.

$$t = \frac{\beta_k^{ML}}{Var[\beta_k^{ML}]^{\frac{1}{2}}} \tag{5}$$

This test evaluates the null hypothesis $H_0\colon \beta_k = 0$, i.e. that the coefficient is zero and the estimate β_k^{ML} differs from zero only because of sampling error. Under the null, the t-statistic is assumed to follow a standard normal distribution. The null hypothesis is rejected at significance α if the t-statistic falls outside the critical values.

The overall goodness of fit of the model must be assessed using appropriate statistics and tests that evaluate how well the model reproduces observed choices. A statistic commonly used to account for possible fluctuations in model performance: the McFadden Pseudo ρ^2. This measure compares the calibrated model, with log-likelihood $L(\beta)_{ML}$, to a model with no explanatory power (all coefficients equal to zero), characterised by *L(0)*. It is defined as:

$$\rho^2 = 1 - \frac{ln\, L(\beta^{ML})}{ln\, L(0)} \tag{6}$$

A value of ρ^2 close to zero indicates poor predictive capacity, meaning the model is little better than the basic model with all coefficients set to zero. Conversely, ρ^2=1 represents a model able to perfectly reproduce users' choices. More broadly, the main usefulness of this statistic is as a yardstick for comparing different models (McFadden, 1973).

Another interesting test for model validation is the likelihood ratio test on coefficient vectors. It tests the null hypothesis that β is equal to a β^* vector, which can also be defined indirectly by imposing some constraints on the β vector. In any case, β^* is the vector that maximises the log likelihood function subject to the constraints considered. The null hypothesis $H_0\colon \beta = \beta^*$ can be tested using the Likelihood Ratio statistic LR

$$LR(\beta^*) = -2[lnL(\beta^*) - lnL(\beta^{ML})] \tag{7}$$

which under the null hypothesis is asymptotically distributed according to a χ^2 variable with a number of degrees of freedom equal to the constraints imposed in estimating β^*.

The study was conducted using a recursive method in which each model was specified, calibrated, and validated. For each iteration, the methodological scheme is shown in Fig. 2

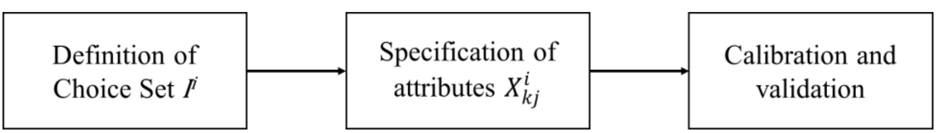

Fig. 2. Methodological scheme

4. Results

4.1. Case study analysis

This section presents an implementation of the proposed methodology, focusing on a case study of a DRT service operating in southern Italy. The area considered is the province of Ragusa, in Sicily. The service connects 3 small mountain towns (namely Chiaramonte Gulfi, Giarratana and Monterosso Almo) with the main city centre of the province, Ragusa. The service operates as a “Hub & Spoke” service, in which customers may travel from one of the minor towns to the main hub, and vice versa; it is not possible to trip from a minor town to another minor town.

The aim of the service is to offer additional mobility options to residents of the three peripheral areas, improving their accessibility. Among the objectives of the managers, there is the increase of the possibilities of movement for users from the suburbs towards the centre to carry out afternoon activities. The service area is represented in Fig. 3.

Ragusa is the main city of the province and there are located the main services (secondary schools, hospitals, sanitary structures, railway station, etc.); the tree small town are placed in a mountainous area and suffer for depopulation and lack of services.

Scheduled LPTs between the towns and the main city is operating mainly in peak hours to guarantee connectivity for students for ordinary lectures at school, but leaving the afternoon completely uncovered.

The service wants to integrate the connections, allowing residents in the three municipalities to reach the main city in the afternoon hours.

The service operates from Monday to Friday, from 3.00 pm to 9.00 pm. The scheme of the service is semi-rigid: users may book a ride choosing pickup and delivery point from a set of stops in the area considered.

If the pickup point is placed in one of the minor towns, the delivery point must be in the main city; and vice versa.

Data available for the study are:

- Booking identification
- Pickup point
- Pickup time (requested and realised)
- Delivery point
- Delivery time (requested and realised).

For privacy reasons, each booking isn’t related to consumer’s characteristics.

The data set considered in the work refers to the period between October 2024 and February 2025. In the period considered, 207 booked trips were stored. The number of observations (207 trips) reflects the experimental nature of the service, which has only been operational for a few months. The study therefore focuses on the initial launch phase, providing initial empirical evidence of the dynamics of adoption and use of a DRT in a rural context (König, A., & Grippenkoven, J. ,2020)The data collected does not yet reflect consolidated demand but describes the service's launch phase. The study should therefore be interpreted as an exploratory analysis of early adopters and emerging patterns. This work represents an initial contribution based on data collected during the launch phase. The data considered in this paper refer to all trips made by users of the DRT service. The overall order of magnitude of this dataset is equivalent, on average, to one month of launch in other DRT systems (e.g., Caramuta et al., 2025); the dataset used is a census-based survey, which means it considers all trips made. The difference in order of magnitude can be explained by the different levels of economic development and population density of the areas considered. As the service continues, it will be possible to update the model based on broader data bases, improving its robustness and predictive power. Similar evaluations have been conducted on samples of less than 500 observations (Wang et al., 2015).

The dataset does not include user sociodemographic information (age, gender, income, and travel purpose). This represents a significant limitation, as the literature shows that these variables are among the main determinants of DRT service adoption. The lack of this data stems from the data collection method, which focused primarily on operational aspects (origin, destination, bus availability). The primary objective was to monitor the operation and sustainability of the service, rather than to profile users' socioeconomic profiles. Consequently, the study does not aim to explain DRT adoption at the individual level, but to provide initial evidence on structural and operational factors related to initial demand (e.g., the role of trip origin and the availability of transport alternatives).

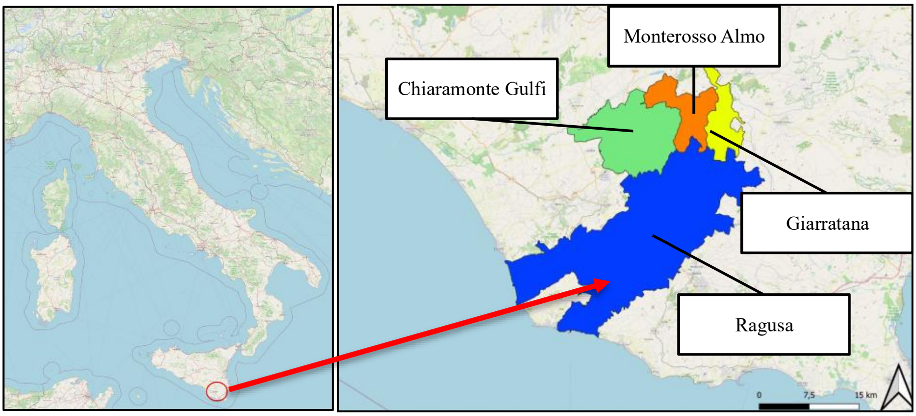

Fig. 3. Study area and municipalities connected by the DRT service (Source: author's elaboration base on QGIS and OpenStreetMap (*Ggis.org; OpenStreetMap*))

The service is mainly designed for those who need to travel from peripheral centres to the main hub. Generally, the aim of the service is to improve mobility related to occasional or systematic trips involving afternoon activities in the main hub. The aim of the model calibrations is to estimate how trip patterns relate to different time slots and how these probabilities change from one time slot to another.

4.2 Specification, calibration, validation

To understand which variables best explain the choices made, different specifications of the model were tested. Each specification of the model was characterised by two elements: a different set of alternatives and a different set of attributes. Regarding the alternatives, various combinations were tested, using different time slots. The service operates from 3 pm to 9 pm, from Monday to Friday. Different time slots were tested. The models with greater discretisation showed a lower significance of the attributes and lower values of the validation indicators; furthermore, in the attempt to identify homogeneous time slots, it emerged that there are no significant differences between some time slots. The most efficient combination that best explains the phenomenon, starting from the known characteristics, is the one that divides the afternoon into two time slots: before 6 pm and after 6 pm.

Each specification of the model also requires a definition of the attributes. Considering the available data, attributes were tested that allowed to identify differences based on the areas of origin and destination of the movements, on the days of the week, on the presence of complementary services. Some characteristics emerged. In general, among the various calibrations tested, no significant differences emerged, in the choice of time slots, between the different days of the week, thus indicating a generally homogeneous use between the various days, with the exception of Thursday. Similarly, attributes connected to the areas of origin and destination and to the presence of complementary services emerged. This preliminary result can be traced back to the substantial social and cultural homogeneity between the three towns, which share, in addition to their distance from Ragusa, territorial characteristics and low public transport density.

Most of the tested attributes were found to be non-significant: no significant differences were found among stops and weekdays in the selection of one time slot over another.

Calibrations were performed on R (R Core Team, 2025), using the mlogit package (Croissant, 2012; Croissant, 2020 a; Croissant 2020 b), and validated on Microsoft Excel (*Microsoft Corporation, 2025*). The territorial analyses on the geographic data were carried out on QGis *(QGIS, 2025)*.

As discussed, the calibrations results indicated that the alternative scheme that best represents the phenomenon is the one in which the activity time is divided into two time slots: pickup hour before 6 p.m. and pickup hour after 6 p.m.

The choice tree of the binomial model is illustrated in Fig. 5. The calibrated models are binomial logit models used to represent time slot choice. Eq. (8-9) provide the specification of the probabilities (common to all the models), while Eq. (10-12) express the systematic utility of the alternatives in the different models.

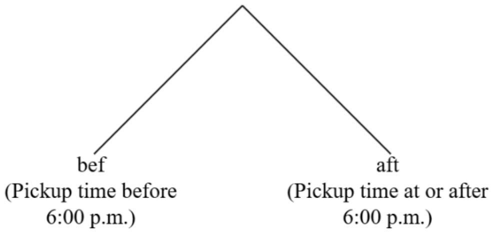

Fig. 5. Model 2, proposed model tree choice

$$p(aft) = \frac{e^{V_{aft}}}{1+e^{V_{aft}}} \tag{8}$$

$$p(bef) = 1 - p(aft) \tag{9}$$

$$V_{aft} = \beta_{HUB}HUB + \beta_{AVL}AVL + \beta_{ASA}ASA_{aft} \tag{10}$$

$$\begin{aligned} V_{aft} &= \beta_{HUB}HUB + \beta_{AVL}AVL + \\ &+ \beta_{SEASON}SEASON + \beta_{ASA}ASA_{aft} \end{aligned} \tag{11}$$

$$\begin{aligned} V_{aft} &= \beta_{HUB}HUB + \beta_{AVL}AVL + \\ &+ \beta_{SEASON}SEASON + \\ &+ \beta_{MID\_WEEK}MID\_WEEK + \beta_{ASA}ASA_{aft} \end{aligned} \tag{12}$$

Where:

- HUB is a dummy variabile. Its value is 1 for trips with origin in Ragusa, 0 otherwise.
- β_{HUB} is the calibrated parameter of the attribute OR.
- AVL is a dummy variable. Its value is 1 if at the booked pickup time, there were no alternative PT service journeys available for the same origin-destination, 0 otherwise. For the characteristics of the PT service, reference was made to the public transport companies operating in the municipalities studied (*Etna Trasporti; Ast Sicilia*)].
- $SEASON$ is a dummy variable whose value is 1 if the trip takes place in winter, 0 otherwise.
- MID_WEEK is a dummy variable whose value is 1 if the trip takes place on Thursday, 0 otherwise.
- β_{AVL} is the calibrated parameter of the attribute $Nbus$.
- ASA_{bef} is the Alternative Specific Attribute of the aft alternative.
- β_{SEASON} is the calibrated parameter of the attribute W.
- β_{MID_WEEK} is the calibrated parameter of the attribute T.
- aft is the alternative "the user indicates a departure time before 6 p.m.".

Calibration results are indicated in Table 1.
In table 2, indicators of validations for the four models are reported. Indicators are evaluated in comparison to an ASA-only models, as indicated by Cascetta, 2013. These results are represented in Fig. 6.

Table 1. Models calibration results

Attribute	Parameter	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
		Model 0		Model 1		Model 2		Model 3	
ASA_{aft}	β_{ASA}	-2.81***	-6.1***	-4.14	-5.85***	-3.46	-4.74***	-3.41	-4.64***
HUB	β_{HUB}	4.41***	8.45***	5.17	7.47***	5.43	7.49***	5.6	7.52***
AVL	β_{AVL}	[-]	[-]	2.05	3.22***	2.32	3.55***	2.4	3.64***
$SEASON$	β_{SEASON}	[-]	[-]	[-]	[-]	-1.41	-2.62***	-1.34	-2.47**
MID_WEEK	β_{MID_WEEK}	[-]	[-]	[-]	[-]	[-]	[-]	-0.84	-1.65*

*->p-value<0.1; **->p-value<0.05; ***-> p-value<0.01

Table 2. Models validation results

Model	Only-intercept	0	1	2	3
Log-Lik	-143.48	-73.079	-65.471	-61.59	-60.283
ρ^2	0	0.49	0.54	0.57	0.58
LRT	[-]	χ^2=140.8 p.value < 0.01	χ^2=156.02 p.value < 0.01	χ^2=163.78 p.value < 0.01	χ^2=166.39 p.value < 0.01

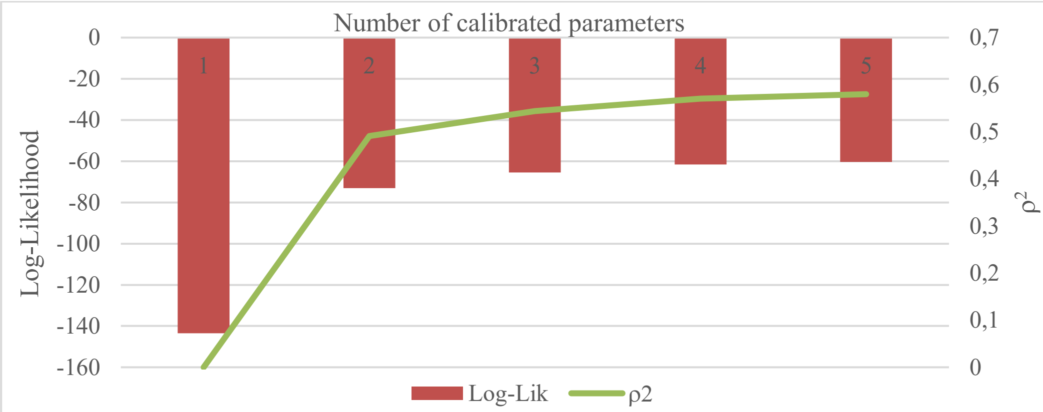

Fig. 6 Comparison of validation results between the different models

5. Discussion

Models with attributes with significance levels at least 0.1 have been reported.

The models described show a progressive increase in the number of attributes and, at the same time, a progressive increase in the significance of the results and the values of the validation indicators. All models show high ρ^2 values and significant LRT with a p-value <<0.01. Furthermore, the specifications progressively add new attributes, while ensuring stability in estimation and significance; the attributes' signs do not undergo modifications and, at the same time, their absolute value remains almost unchanged.

The most relevant attribute in the choice of the time slot is the area of origin, highlighting how users choose the time slot mainly on the area of origin and therefore, for the characteristics of the service, on the direction and sense of the journey. The model highlighted that the variable *HUB* is the one that has the greatest significance and contributes positively to the utility to start a trip after 6 p.m. This indicates that the service is used mainly for one-way trips (from the villages to the city) in the early afternoon, and for opposite-direction trips in the later afternoon. The result takes into account that origin also implies the direction of travel, consistently with what is defined in Section 3 regarding the structure of the service; however, no significant differentiation emerges between the different destination cities, whose different contributions have been tested without evidence of significance. The calibrations were evaluated considering these contributions but were not reported because they were not significant; it is useful to consider how, therefore, the contribution on the origin/destination of the journey is prevalent compared to other potential contributions. In fact, Model 1, in which in addition to the ASA only the attribute related to the origin of the displacement is present, already has a very high ρ^2 value (around 0.49), while the subsequent contributions are responsible only for minor improvements in the overall goodness-of-fit. The result supports the hypothesis that the system of activities being served (primarily afternoon school and recreational activities) exhibits similar temporal characteristics in terms of time slot.

The attribute AVL expresses the adoption of the service in conditions in which there are no alternative buses. The attribute has a positive sign for the 6 p.m. – 9 p.m. time slot, thus indicating that a large part of the users chooses the service when, for the relationship or to be travelled, there are no potentially complementary public transport services. The attribute considered therefore highlights a structural characteristic of the system, namely the poor bus coverage in most of the afternoon for some of the routes considered and makes it conceivable that the user may choose the DRT service in this time slot precisely because of the absence of the public transport service.

The other two results are expressed in Model 3 and Model 4. The *SEASON* attribute indicates the winter season and has a negative parameter. The result indicates that, for the months in which the service was operational, there was a decrease in the probability

of choosing the evening time slot compared to the afternoon time slot in winter, compared to autumn; in fact, for the months in which the service was operational, only these two seasons were considered (if autumn, *SEASON = 0*). Finally, the *MID_WEEK* attribute indicates a decrease in demand on Thursdays compared to other days of the week. These two results demonstrate a temporal periodicity in demand, both seasonal and weekly. There are several studies in the literature that consider DRT; most of them, as seen in Section 2, focus primarily on analysing service usage and are, in fact, closely linked to Stated Preference surveys. The analysis conducted in this paper is based on Revealed Preference data. However, some considerations regarding different types of parameters are useful. As in Caramuta et al., a periodicity within the week emerges; in particular, the importance of the day of the week's contribution is noteworthy. Furthermore, Caramuta et al. raises the issue of the different use of the service between the city center and the peripheral areas; in this sense, it is very similar to the structure of the territorial system in the case analysed, characterised by a clear distinction between the various zones; in the study under consideration, there is a temporal differentiation of destinations, with trips to the hub concentrated in the first part of the afternoon and vice versa in the second; in Caramuta et al., there is a greater predilection for trips to the city center.
The results seem to indicate a pattern of service usage in which people move from the outskirts to the centre in the first part of the afternoon and from the centre to the outskirts in the second. It is also probable that a large part of the trips "from the centre to the peripheral zones" in the late afternoon are mainly return trips of users who have already made a first outward trip on the same day. These characteristics are connected to the specified nature of the service in which the trip with origin in one of the smaller municipalities cannot have another of the smaller municipalities as its destination. Furthermore, no significant differences were determined between the three municipalities that would allow the model to assume greater accuracy; the exception is the variable on the absence of buses to make the trip, which effectively reflects the heterogeneous presence of public transport in the municipalities considered.
The results obtained offer a perspective that fits into the scientific literature on the topic. With reference to the research objectives defined in Section 1, the paper has:

– Proposed RUM modeling applied to a constrained DRT service, in which trips are possible only from the city center to the suburbs and vice versa, using data on individual trips as reference data to determine the choice of a specific time slot;
– Applied the methodology to a case study in Southern Italy, from which several significant attributes emerged, primarily related to the origin of the trip within the main hub (city center), the presence of complementary services, and contributions related to the day of the week and the season.

6. Conclusion

This manuscript proposes a methodology to study the adoption time slots in DRT. One of the main characteristics of on-demand services is that they are often linked to areas or time slots with weak demand. This makes traditional predictive models calibrated on peak times and models calibrated for systematic reasons deeply investigated in the literature (home-study or home-work) often inadequate. A major challenge is the difficulty in predicting trip time and trip purpose, mainly for non-dedicated services. The proposed methodology represents a first step in modelling user behaviour in adopting the DRT. In the case study explored in this study, the service is structured around a main hub and some smaller countries.
The proposed model is a time choice sub model, aimed at studying the probability of traveling in one time slot or another. The binomial logit formulation and the specification of systematic utilities reflect the structure of the analysed system, divided into two time slots (before and after 6 p.m.). The model highlights some distinct and clear elements: in the second part of the afternoon users tend to move from the hub to the peripheral areas, and the lack of an alternative local public transport service can have an impact; on this attribute, further investigations could allow to identify how much the behavioural component influences the choice of mode, but it is necessary to compare the DRT mode with other transport modes. Other results obtained from the model indicate periodicities related to the day of the week and the season of the year.

The proposed methodology offers several advantages: the use of the RUM formulation allows to always define relationships between the probability of choice and the individual characteristics of the users. Additionally, the model can be easily integrated with other sub-models, such as the choice of stops. In the calibrated model, the choice of stops did not significantly affect the time slot, and stops have been excluded from the presented specification. A subsequent sub-model of choice of stops, to make hypotheses on the reasons for travel, is currently under investigation.

However, the proposed approach has limitations. The absence of sociodemographic characteristics of individuals from the database restricts the ability to analyse the relationship between user characteristics and the choice alternatives. Moreover, while the proposed model, in its current formulation, is specifically tailored to services with the characteristics described, it remains easily generalisable to other cases. The size of the dataset considered may be increased in the future as additional months of service are completed. This will allow us to simultaneously verify service continuity in other seasons and over a longer period. Among future developments, in addition to the behavioural analysis of users, it is necessary to study models for the analysis of destinations, as defined. The calibrated models will also be tested starting from any new datasets available on the service. Furthermore, the relationship between service attributes and territorial variables will be investigated. The analysis of behavioural and sociodemographic attributes of users will be supported by a new series of surveys to capture individual level data.

This study is valuable to two main categories of stakeholders: academia as it offers a significant contribution on the topic of the analysis of on-demand services; and transport service managers, both fixed route and on-demand responsive, by providing a schematic methodology for the analysis of DRT and highlighting key factors influencing of the choice of time slots.

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