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Designing microtransit services in suburban areas: A case study in Palermo, Italy

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ABSTRACT

Poor quality of Public Transport (PT) services is one of the main causes of social exclusion for people living in the suburbs. Public transport companies usually allocate few financial resources to these areas, providing transport services with low frequency, poor accessibility, poor reliability, and high waiting times at stops. Recently, microtransit has emerged as an effective solution to improve the travel experience in suburban areas, particularly for non-commuting trips during off-peak hours. This paper presents an integrated methodological approach for designing microtransit services to meet the mobility needs of people living in low-density suburbs. By conducting a Reveled Preference (RP) and Stated Preference (SP) survey and developing a travel demand model, the demand was estimated and used as input to simulate and size the service. Combining GIS and simulation models, Key Performance Indicators (KPIs) were assessed; fleet size to meet the trip requests was identified and the fare was selected using a sensitivity analysis. The method was applied to a real case study to design a new microtransit service with flexible routes and on-demand stops in a suburban area in Palermo, Italy. The results highlight how introducing a microtransit service with 30 nine-seater vans could change the mobility habits of people living in the suburban area, being attractive and financially sustainable if costing 2 €, or just a little more than the existing fixed-route bus service. It could improve the travel experience by reducing the average waiting time at stops to around 5 min and improve access to amenities and PT hubs by guaranteeing a walking time of maximum about 8 min.

1. Introduction

Poor quality of conventional Public Transport (PT) services is one of the main causes of social exclusion in suburbs and rural areas. People living in these areas often experience difficulties in reaching desired destinations such as schools, workplaces, food shops and healthcare facilities as well as sporting, leisure, and cultural activities (Stanley & Lucas, 2008).

Resources for PT are limited, thus PT companies usually allocate most of their financial resources to more densely populated areas, where the transport demand is higher; on the other hand, in rural and suburban communities characterized by low-density areas, PT companies often provide transport services with low frequency and reliability, with consequent poor accessibility (Cooke & Behrens, 2017). These communities become highly car-dependent and traffic congestion worsens non-motorized travel conditions; moreover, policymakers tend to be less concerned with the needs of non-drivers. In these contexts, non-drivers face many issues, including limited travel options and high travel times due to poor-quality PT services (Han, Lee, Yu, & Dejno, 2021). Indeed, traditional PT services often cannot effectively and economically meet the mobility needs of people living in low-density areas; this becomes challenging especially for older people, people with disabilities, and low-income people, i.e. groups at risk of social exclusion (MacLeod, Kamruzzaman, & Musselwhite, 2022).

In recent years, a wide range of shared mobility services has emerged to improve the accessibility and social inclusion for people living in low-density areas, operating as feeders to existing high-capacity PT networks, such as metro or rail lines. In this way, shared mobility makes

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access to jobs and other public services easier and more equitable (Shaheen, Cohen, Chan, & Bansal, 2020). Among these services, including carsharing, bikesharing and scooter sharing, microtransit has received increased attention in recent years.

Microtransit, also known as Demand-Responsive Transit (DRT), is "an intermediate form of PT, somewhere between a regular service route that uses small low floor buses and variably routed, highly personalized transport services offered by taxis" (Brake, Nelson, & Wright, 2004). Thus, microtransit is considered a hybrid service that combines the features of conventional buses and taxis. However, Papanikolaou, Basbas, Mintsis, and Taxiltaris (2017) described flexibility and capacity as the main operational features differentiating microtransit from taxis and conventional buses. Taxi has flexible routes, but it can serve a low number of passengers without trip sharing. Conventional buses operate on predefined routes according to a fixed schedule, having no flexibility, but they can serve more passengers. DRT falls in the middle with a greater flexibility than buses and serving fewer people than a conventional bus due to the smaller size of vehicles (i.e., cars, vans, or minibuses).

The introduction of microtransit services in low-density areas, i.e. rural or suburban areas, offers numerous benefits: increased access to essential services; a better travel experience for people with disabilities, older people, and young students; a greater social inclusion (Sörensen, Bossert, Jokinen, & Schlüter, 2021); greater flexibility through combination with other transport services (i.e. with fixed-route services); and a reduction in noise and air pollution (Viergutz & Schmidt, 2019).

According to Shaheen et al. (2020), microtransit is always characterized by one or more of the following features: route deviation (being demand-responsive, vehicles can deviate from a fixed route to meet travel requests); point deviation (vehicles serve a limited number of stops without a fixed route between stops); demand-responsive connections (vehicles operate in a demand-responsive geographic zone with one or more fixed-route connections); request stops (passengers can request unscheduled stops); flexible-route segments (demand-responsive service is available within segments of a fixed-route); zone routes (vehicles operate along a route corridor). All these aspects, related to service operational features and users' needs, make the design procedure of a microtransit service complex. Determining the proper number of vehicles needed to meet demand without oversizing the fleet (which increases costs) or undersizing it (which worsens the service) is a significant challenge. Indeed, on the one hand, minimizing waiting times for passengers and ensuring that vehicles arrive on time is crucial for user satisfaction; on the other hand, establishing a pricing model to be competitive but also cover operating costs is difficult.

Within this framework, this paper aims to describe an integrated methodological approach for the design of microtransit services in suburban areas, using a mode choice model calibrated by stated preference (SP) surveys to estimate the users' requests, and implementing a simulation model to simulate the service and optimize the fleet size, considering the number of travel requests that can be served and the travel time experienced by passengers. Therefore, several simulations were performed, considering the demand (i.e. O/D matrices) estimated through RP/SP surveys and a travel demand model as input data. The implemented simulation model, based on a Geographic Information System (GIS) platform, led to the optimization of the service by identifying the number of vehicles needed to meet the demand. Finally, an objective function with constraints was used to perform a sensitivity analysis and set the best microtransit fare, considering customers, community, and operator perspectives.

The methodological approach was tested considering a real case study, i.e. a suburban area in Palermo, Italy, where a low number of bus lines with low frequency makes PT inadequacy evident.

The paper is organized as follows. Section 2 gives a brief overview of the methods for designing DRT services, and the consequences of the introduction of microtransit in suburban areas. The method we developed is outlined in Section 3. In the Section 4, the case study is presented. After describing the steps to estimate the number of trip requests generated by the study area, the results of the simulation model are analyzed in Section 5, setting the fleet and the fare through a sensitivity analysis. Our conclusions are drawn in Section 6.

2. Literature Review

At the beginning of their introduction, on-demand services were seen as social services rather than a legitimate public service: they were used just by some social groups (e.g. older people, people with disabilities, students, etc.) and received high subsidies (Papanikolaou et al., 2016). These services provided not very flexible travel plans and were used in low-density suburban areas primarily for leisure-related trips. They were often criticized for their high operational costs, their lack of flexibility in route planning, and inability to handle many trip requests. However, the rapid and well-established development of telecommunication and information technology supported the implementation of DRT services, with more efficient and flexible schemes, and a dynamic management of travel requests and vehicle routing (Sörensen et al., 2021).

To design a DRT microtransit service which yields a reduction in car trips, the service area should not be limited to the city centre, but rather cover a typical commuting area, including suburbs. In this way, introducing this service, people living in suburbs can become less car dependent. Some literature works pointed out that the neighborhood of residence has influence on the potential risk of exclusion (Stanley, Hensher, & Stanley, 2022). In this regard, suburbs and rural areas are often characterized by both social disadvantage and transport disadvantage (Lucas, 2012). The implementation of microtransit services can represent a way to improve the capacity to move within these areas, prevent social exclusion and reduce the transport disadvantage, by providing accessibility to Points of Interest – POIs (i.e., amenities and transportation hubs) and enhancing the quality of life (Brumfield, 2023). Thus, microtransit may help to reduce gaps in employment accessibility between low-income zero-auto households and high-income communities, helping transit-dependent households to reduce travel times and access to workplaces more quickly and easily (Bills, Twumasi-Boakye, Broaddus, & Fishelson, 2022).

Several studies focused on microtransit applying different methodological approaches to forecast the demand and simulate the service, evaluating the impacts in transport mobility, social equity and acceptance of the service among different users.

Coutinho et al. (2020) analyzed the impacts deriving from the conversion of a fixed bus line in a demand-responsive system within a rural area of Amsterdam, in terms of distances, number of passengers, costs, emissions, and user perceptions. Their findings showed that the GHG emissions per passenger were lower. Moreover, the system was also well positively perceived by users and reliability was a determinant of satisfaction with the microtransit system.

Wang, Quddus, Enoch, Ryley, and Davison (2015) conducted a customer survey and developed an ordered logit model to assess the propensity to use a microtransit service in the rural area of Lincolnshire in U.K. The authors found that females and elderly people have the highest probability to make more frequent trips using microtransit to go shopping or attend medical appointments.

Nyga, Minnich, and Schlüter (2020) performed an online survey to assess the willingness to pay of different users' groups for door-to-door microtransit services. They found that women, employed and low-income users are willing to pay more for the DRT service. In addition, willingness to pay is closely related to environmental friendliness, especially in rural areas. Moreover, they concluded that the fare should cover costs as far as possible, be socially acceptable, and attract a sufficient transport demand for minimizing external effects.

The study of Kaddoura, Leich, and Nagel (2020) focused on the impacts of both fare and service area design on microtransit in the Greater Berlin area. In several simulation experiments, a significant modal shift of users from conventional PT services to microtransit was registered, highlighting this positive effect from the users' perspective, as users experienced reduced travel time and obtained higher utility.

Bruzzone, Scorrano, and Nocera (2021) provided a citizen focus groups and a cost analysis to analyze the integration of a microtransit system with e-bikesharing and PT in a suburban area of Valenje, Slovenia. The interviewees complained about the low quality and poor efficiency of the bus service. Moreover, due to the morphological condition of the area and long distances, bicycle use was also reduced. The solution of a semi-flexible microtransit service combined with the e-bikesharing service allowed to connect isolated urban areas to the train station with a single integrated ticket. The results of the study also showed that, with funding levels comparable to the existing conventional bus system, a combination of microtransit system and e-bike system could be realized by offering extended service hours to increased users, also improving access to high-capacity transportation hubs.

As regard the microtransit service simulation, Costa, Cunha, and Oliveira Arbex (2021) developed a NP-hard optimization problem to simulate a microtransit service in São Paulo, Brazil, and compare it with traditional PT in terms of service level, average occupancy, and total travelled distance.

Although the authors estimated lower travel times for buses than those associated with the microtransit service, the latter has more reliable waiting times and reduced walking distances. Additionally, microtransit service can be an opportunity to attract users, offering a higher level of service than buses, at a competitive cost: by proposing six-seater vehicles, a 20 % reduction in cost per passenger could be achieved. Nevertheless, the employed combinatorial optimization problem becomes exponentially increasing in difficulty as the instance size becomes larger, thus requiring complex and efficient algorithms and heuristics to solve the dispatching when the trip requests are made in advance and handled together before the departure of the vehicles.

Viergutz and Schmidt (2019) used an agent-based simulation to compare a stop-based microtransit service and a door-to-door service with a conventional bus service in a rural area in Germany. The authors found that waiting and in-vehicle times for customers using the stop-based DRT services are half of those experienced by the users of the conventional bus service. However, to serve the same number of users, the DRT services need a larger number of vehicles and drivers, resulting in higher costs for the operator.

Similarly to the integration of microtransit service for the connection with a transport hub in a suburban area proposed by Bruzzone et al. (2021), the study of Scheltes and de Almeida Correia (2017) presented an agent-based simulation model to study a system for first mile/last mile connection to mass PT modes, provided with on-demand AVs. They implemented a dispatching algorithm to distribute travel requests among the available vehicles using as reference the Renault Twizy, which is a small electric vehicle with a capacity for one passenger. Anyway, the limitation is represented by the absence of trip sharing among users, which make the system only able to compete with the walking mode.

Shen, Zhang, and Zhao (2018) proposed and simulated via an agent-based model an integrated AVs and PT system, with a maximum of four passengers, based on organizational structure and demand characteristics, considering peak hours.

These works used agent-based simulation models, which are complex and often require high computational capacity to simulate the behaviour of millions of agents, being time-consuming and demanding in terms of computational resources. Additionally, the validation may be tricky, and it can be difficult to compare the output of the model with real empirical data.

Considering the microtransit demand, the study of Shen et al. (2018) is based on empirical travel demand and transit operational details derived from the smart card data in Singapore. Similarly, Ma, Chow, Klein, and Ma (2021) evaluated the introduction of a microtransit service in Luxemburg, conducting the study based on a real data set shared by the transport company for a period about a semester. Nevertheless, in low-density areas a low demand is associated with PT, so it is important to be able to estimate the potential demand attracted by a microtransit service. Indeed, the current demand for an existing PT service in suburban areas may not correspond to the demand for a microtransit to be implemented that could improve the performance and reliability of the transport service.

In this regard, we considered the application of RP and SP methods, based on data collected through surveys that can be analyzed using less computationally demanding standard statistical techniques. RP and SP surveys were already used to investigate the factors affecting the microtransit choice (Hussin, Osama, El-Dorghamy, & Abdellatif, 2021; Rossetti, Broaddus, Ruhl, & Daziano, 2023). However, we included RP/SP surveys in a wider methodological framework, using them as inputs for developing a travel demand model and forecasting microtransit demand.

Moreover, both works of Scheltes and de Almeida Correia (2017) and Shen et al. (2018) proposed the introduction of new transport services based on the use of AVs. Nevertheless, the integration of such vehicles could represent a challenge in suburban areas both for road infrastructure and signage, complexity in social interactions and legal frameworks linked to the context analysis. This can be further configured as a limitation since the major costs associated with a transport system are the operational ones, which include the drivers' costs.

Sayarshad and Chow (2015) introduced the service pricing under the assumption of elastic demand to derive the optimal fleet size and maximize social welfare. Therefore, we considered an analysis of the financial economic sustainability of the service modelling a microtransit service demand with different timing and spatial distribution.

We also introduced the possibility of trip sharing respect to the study of Scheltes and de Almeida Correia (2017), incrementing the vehicle capacity fixed to a maximum of 6 passengers by Sayarshad and Chow (2015), thus considering 9-seater vehicles to favour trip sharing, limit the number of vehicles needed to perform the service and reduce the costs.

In summary, the novelties we want introduce in our research are related to (i) rigorous microtransit demand modelling through RP and SP data; (ii) economic and financial analysis to design microtransit service considering trip sharing; (iii) testing the methodology within low-density suburban areas during off-peak hours in Italian context.

In this paper we propose an integrated methodological approach to design microtransit services considering a comprehensive perspective of the economic and financial factors related to microtransit, i.e. service operational parameters; user satisfaction; fares; service costs and externalities. Starting from RP and SP data (derived from a survey deeply detailed in Capodici, D'Orso, Migliore and Vittorietti, 2024), we developed a four-stage model to estimate the microtransit demand, characterized by an iterative procedure between the demand modelling and service simulation to ensure waiting and walking times meeting the users' needs, improving accessibility to POIs and quality of life. Additionally, we also included in our microtransit design methodology the fare setting problem, performing a sensitivity analysis and determining the fare to be selected.

Suburban and rural areas with low population density require a different service design than urban areas (Schasché, Sposato, & Hampl, 2022). Thus, to the best of our knowledge, we are the first to consider an on-demand service operating in low-density areas, which integrates the PT during off peak-hours in a suburban area of an Italian city. Specifically, we decided to test our methodology considering a stop-based service that serves as a feeder system to a high capacity and high regularity transportation hub, connecting suburbs to the city center.

3. Method

The methodological approach to design the microtransit service in suburban areas is multi-step, as schematized in Fig. 1:

1) Identification of the study area and zoning;

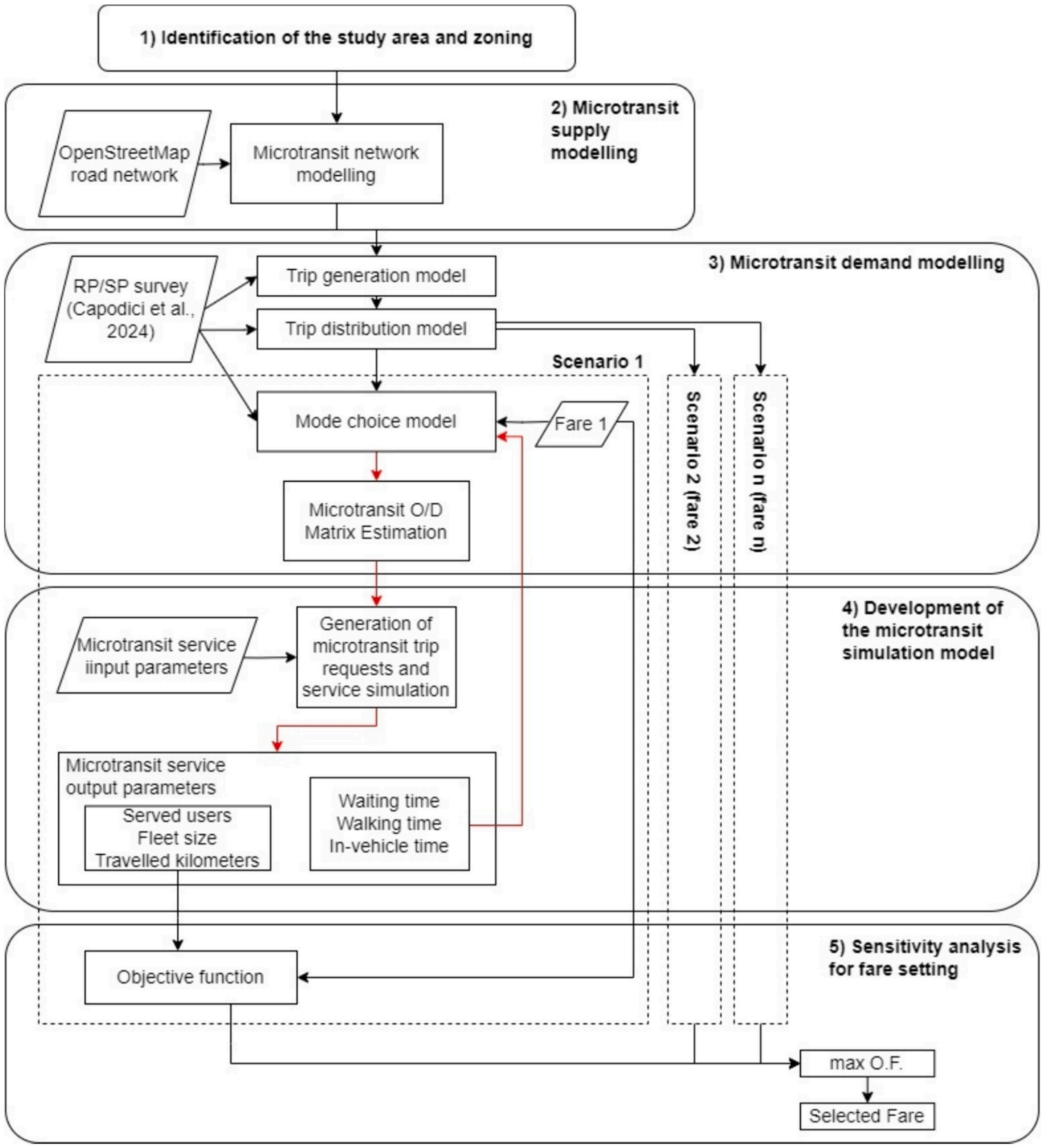

Fig. 1. Methodological framework.

2) Transport supply modelling: building the road network and the microtransit network;

3) Microtransit demand modelling: RP/SP surveys, mode choice model and OD matrix estimation for non-commuting trips made by microtransit;

4) Development of the microtransit simulation model, simulation and scenario evaluation through Key Performance Indicators (KPIs) and comparative analysis, in order to identify the fleet size based on demand for microtransit;

5) Sensitivity analysis based on an objective function to identify the fare to be selected.

A detailed description of each methodological steps is reported in the next subsections.

3.1. Identification of the study area and zoning

The *first step* is the identification of the study area and the definition of the zoning scheme to divide the study area into smaller zones, usually coinciding with census blocks, block groups or census tracts. All trip origins and destinations are represented at the spatially aggregate level of the movement from an origin zone to a destination zone. Thus, a centroid is assigned to each zone and considered as source of each trip starting in this zone. External centroids are also defined to represent the main traffic generators and attractors outside the study area.

3.2. Transport supply modelling

The *second step* is the modelling of the transport supply, consisting of building the road network in a GIS software, to constitute the base network of the simulation model. The road network consists of links (roads) and nodes (road intersections). The links are weighted by their corresponding road lengths. Then, the next step is the microtransit network definition. In this phase, the type of microtransit service to implement (or simulate) in the study area must be identified: a door-to-door service (without predefined stops), a stop-based service with flexible routes, or a stop-based service with fixed routes and some detours. Thus, the main features of the microtransit service must be defined (vehicles performing the service, presence of predefined stops, presence of fixed routes and detours). For example, considering the vehicles' size, roads where microtransit vehicles can't circulate must be identified and excluded from the microtransit network. In the case of a stop-based service with flexible routes, the Pick-Up and Drop-Off nodes need to be identified. Moreover, in the case of a stop-based service with fixed routes and detours, they also need to be identified.

3.3. Microtransit demand modelling

The *third step* consists in modelling the microtransit demand in the study area. To do this, using a combination of RP and SP surveys could be useful. RP surveys are used to record the mobility behaviour that users adopt at the present time. Conversely, the SP survey collected the mode choice decisions of the respondents under future scenarios; thus, it can be used to predict the behaviour of the users when a service does not yet operate in the study area. Conducting RP and SP surveys at the same time allows assessing the mobility habits of people living in the study area and their propensity to use microtransit in the future.

Using the findings of the RP/SP surveys, a traditional transport demand model can be developed and calibrated. The transport demand model consists of a set of sub-models: trip generation model, trip distribution model, mode choice model, and trip assignment model.

The demand for microtransit can be presented by an origin-destination (OD) matrix. In the OD matrix each cell represents the number of trips per day from an origin zone (row) to a destination zone (column). There are many methods to determine the trips generated by a zone. In conventional ways, we can count these trips by conducting a survey.

We can also develop a trip generation model, with dependent and independent variables. The total number of person-trips generated by a zone is the dependent variable; on the other hand, the independent variable consists of household and socio-economic factors, which influence the trip making behaviour of users.

Thus, we can assess the average number of trips per day made by users belonging to a certain socio-economic group. In this regard, trips per day generated by a zone can be estimated using census data and trip generation rates for user groups. The trips generated from each zone are attracted to the other zones based on a trip distribution model.

These trips may be within the study area (internal-internal) or between the study area and areas outside the study area (internal-external). There are several methods to distribute trips among zones; the most widely used trip distribution model is the gravity model. According to this model, the number of trips between two zones is directly proportional to the ability of the zone of destination to attract trips and inversely proportional to a function of travel time between the two zones. The ability of a zone to attract trips can be estimated as a function of the number of employees or services existing in that zone.

Knowing the non-commuting trips per day attracted by each zone, we can calculate the OD matrix. We have as many matrices as the socio-economic categories of users considered.

Finally, for each user group, the microtransit OD matrix, considering the trips made by microtransit by this user group can be calculated as a fraction of the total OD matrix, considering all the trips made by this user group. Indeed, the next step is the development of a mode choice model to assess the choice probability for microtransit for different groups of users. Many models can be used to assess the choice probabilities: multinomial logit models, conditional logit models, mixed logit etc. In the case study presented in Section 4, we specified the use of a multinomial logit model. The choice probability for microtransit for a specific user group can be calculated for each OD pair. For each user group, we can assess each element of the microtransit OD matrix multiplying the corresponding element of the total OD matrix, i.e. the number of trips from zone o to zone d, by the choice probability for microtransit for the o-d pair. This step must be repeated for all the considered user groups. Thus, the daily microtransit OD matrix is the sum of the microtransit matrices for every user group. Each element of the matrix is the number of trip requests that users can express to make a trip from a zone to another.

Finally, the trip assignment stage is developed using a simulation-based approach.

3.4. Development of microtransit simulation model

The *fourth step* implies the development of the microtransit simulation model which consists of two procedures: (i) the creation of trip requests and (ii) the creation of paths.

The first procedure starts from the disaggregation of the demand on the network nodes to generate travel requests.

The demand associated with the microtransit service, determined in the third step, is represented within a "Zone Based" matrix which is associated with the macroscopic model. To simulate the service, it is necessary to associate this demand with a microscopic model. The transition from a macroscopic "zone based" model to a microscopic "node and time based" model requires the disaggregation of the demand from zones to nodes. In this way, each trip will have an origin node and a destination node. Once the demand has been disaggregated, we proceed with the creation of the list of the trip requests, which will be processed during the simulation of the service.

For the trip requests' generation, it will be necessary to define the following input parameters:

- duration of the service (time interval of the day);
- travel request aggregation rate;
- pre-booking time;
- maximum waiting time.

After the definition of these parameters, it will be possible to generate the list of requests having the desired characteristics to be associated with the service. For each request, we will have identified the origin and destination nodes of the trip, the time at which the request is made, the scheduled pick-up time and the total number of passengers (in the case of passengers traveling together).

The second procedure consists of the creation of paths. Once the list of trip requests has been defined, it will be necessary to plan the operational service in order to satisfy all requests. This is carried out through a "Dispatcher" procedure (see Fig. 2). The procedure is based on assigning the trip request to the closest vehicle available to arrive within the maximum waiting time, defined for each request.

During the procedure, to facilitate the sharing of the vehicles, priority is always given to "active" vehicles, i.e. vehicles that already have passengers on board.

Considering each available vehicle, the ideal travel time (ITT) and the detour time (DT) are calculated for each passenger. The ITT represents the time required to make the trip between origin and destination, considering the shortest path without any stops. DT is defined as the additional time due to the detour required to collect additional trip requests.

Through the following equation it will be possible to calculate the detour factor (DF) associated with each passenger. Thus, the DF is a non-dimensional factor used to quantitatively evaluate the DT in relation to the ITT, according to Eq. 1:

$$DT = (DF - 1) \bullet ITT \tag{1}$$

Within the procedure, it is necessary to define the following qualitative service attributes:

- All accepted detour time (all. Acc. DT), represents the minimum value always accepted of DT in addition to the ITT;
- Maximum detour time (Max DT) represents the maximum DT value accepted by the user in addition to his ITT;
- Maximum detour factor (Max DF) represents the maximum deviation factor accepted by the user in relation to his ITT.

Once these parameters have been defined based on the characteristics of the service, it will be possible to start the Dispatcher procedure, and three conditions can occur:

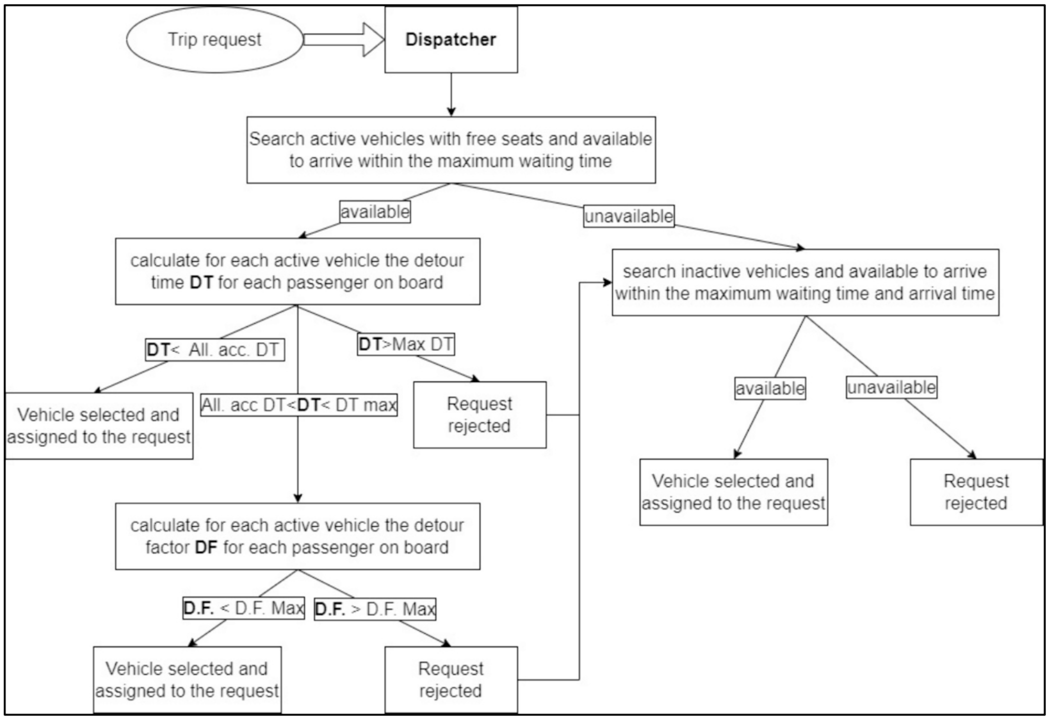

Fig. 2. Dispatcher procedure.

- If: $DT < all.acc.DT$, it is not necessary to check the DF and the vehicle will detour from the scheduled route, satisfying the trip request it has received;
- If: $all.acc.DT < DT < Max\ DT$, it is necessary to check the DF. If the DF values do not exceed the maximum accepted DF, the vehicle will proceed to make the deviation of the scheduled route, satisfying the travel request it has received. If, on the other hand, the maximum DF is exceeded, a search will be carried out among "inactive" vehicles, i.e. vehicles which are stationary with no passengers on board at that moment of the trip request, but which are still available to provide the service. If one of the vehicles can satisfy the trip request respecting the value of the maximum DF, then the request will be satisfied, otherwise it will remain unsatisfied.
- If: $Max\ DT < DT$, it is not necessary to check the DF and a search will be carried out directly among "inactive" vehicles, i.e. vehicles which are stationary at that moment with no passengers on board, but which are available to provide the service. Similarly, to the previous condition, if one of the vehicles can satisfy the trip request respecting the value of the maximum DF, then the request will be satisfied, otherwise it will remain unsatisfied.

These conditions must be verified and satisfied both for the passenger who made the request and for each passenger on board: only in this way the trip request can be satisfied.

This "Dispatcher" procedure, which serves individual requests based on the order in which they were generated, depends on the input parameters reported in Table 1.

After these procedures and configurations, it is possible to simulate the service by running the simulation model. We can perform several simulations varying the microtransit demand for different fare values (e.g. Scenarios 1, Scenario 2 and Scenario n in Fig. 1). Indeed, the fare impacts on the choice probability for microtransit and, consequentially, on the microtransit O/D matrix used as input in the simulation model. After simulating the service, a scenario evaluation can be made through Key Performance Indicators (KPIs) to evaluate the performance of the service and optimize the fleet according to demand. The list of simulation output parameters is reported in Table 2.

Table 1
Input parameters for the dispatcher procedure.

INPUT parameters	Description
I1 –DRT matrix	Number of DRT travel requests [pass]
I2 –Max vehicles	Maximum number of vehicles used to perform the DRT service [vehicles]
I3 – Seats	Number of available seats for each vehicle [pass]
I4 – Max DF	Maximum Detour Factor, defined as the ratio between the travel time with the deviations due to the sharing and the direct travel time [dimensionless].
I5 – Max DT	Maximum Detour Time due to the sharing [min,*sec*].
I6 – Min DT	Minimum Detour Time due to the sharing [min,sec].
I7 – All acc DT	Detour Time value always accepted [min,sec]
I8 – Max wait	Maximum waiting time at the DRT stop [min,sec]
I9 – Max O/PUDO walk	Maximum walking time to cover the distance between the origin and the DRT stop (PUDO) [min,sec]
I10 – Max PUDO/D walk	Maximum walking time to cover the distance between the DRT stop (PUDO) and the destination [min,sec]
I11 – Boarding Time	Time needed to board and alight a vehicle per passenger [min, sec]

The simulation output parameters must be consistent with the mode choice model input parameters (i.e. waiting time, walking time, in-vehicle time). Otherwise, the procedure must be iterated until convergence (see the loop represented in Fig. 1 by red arrows).

3.5. Sensitivity analysis

The *fifth and last step* is the sensitivity analysis to set the fare. This sensitivity analysis is performed using an objective function with constraints.

Considering the discrete set of possible fares used in the definition of the scenarios, the best fare can be estimated by maximizing the objective function (Eq. 2), taking into account the equilibrium among fare, modal split and fleet size (see Fig. 1):

$$Argmax(f) = Surplus_{users} + Revenues_{DRT} - Cost_{operating\ DRT} + Externality \tag{2}$$

Table 2
Output parameters for the dispatcher procedure.

OUTPUT parameters	Description
P1 –DRT requests	Number of trip requests satisfied by DRT [pass]
P2 – Experienced DF	Detour Factor experienced by the users
P3 – T wait	Average waiting time at the DRT stop [min,*sec*]
P4 – T O/PUDO	Average walking time to cover the distance between the origin and the DRT stop [min,sec]
P5 – T PUDO/D	Average walking time to cover the distance between the DRT stop and the destination [min,sec]
P6 – In-vehicle DT	In-vehicle Detour Time [min, sec]: additional in-vehicle travel time experienced by the users
P7 – Vehicles	Number of vehicles used to perform the DRT service [vehicles]
P8 —V DRT	Average travel speed of the DRT vehicle [km/h]
P9 – Km all	Number of kilometers travelled by all DRT vehicles [km]
P10 – Pass all	Average number of passengers per vehicle served by the service [pass]

subject to the constraints:

$f_{min} \leq f \leq f_{max}$.

where f_{min} and f_{max} are within an admissible range for the urban context, and where:

- the term "Surplus$_{users}$" shows the user's "surplus", expressed as the product of the total demand and the variation in satisfaction between the project scenario and the initial one, then divided by the coefficient to express the surplus in Euros; the satisfaction could be calculated using the *logsum function* (user maximum perceived utility) for each o-d pair, if we have calibrated a random utility model for the mode choice model;
- the term "Revenues$_{DRT}$" shows the revenues of the microtransit system, considering the fare paid by the microtransit users and the fare paid by the users who move from the private to the PT system; the revenues of the microtransit system depend on the number of trip requests satisfied by the service.
- "Cost$_{operating\ DRT}$" shows the additional operating costs due to the expansion of the PT system using microtransit; the operating costs depend on the number of vehicles used to perform the DRT service and the number of kilometers travelled by the DRT vehicles.
- the term "Externality" shows fewer externalities due to the transfer of a part of the demand from the private car to the PT system. The externalities depend on the number of kilometers travelled by the DRT service.

4. Case study

The proposed methodology has been tested to a real case study to understand the performance of the system depending on several operational parameters and demand scenarios. We present the steps followed to design a new microtransit service in a suburban area of the city of Palermo (Italy).

4.1. Study area

The study area encompasses the neighbourhoods of Tommaso Natale and Partanna Mondello, located in the northern part of the city of Palermo (Italy), and the small seaside villages of Mondello and Addaura. Therefore, the study area covers an area of about 10.5 km^2, which is characterized by poor-quality PT services and a discontinuous urban fabric. As we can see from census data in Table 3, a total population of 27,789 lives in the study area in 2021. About 26 % of the residents belong to the over-60 age group.

The area is almost purely residential with few traffic attractors such as a shopping mall, some restaurants, beaches, and sports centers. According to the Industry and Services census conducted in 2011 by ISTAT, the study area has a relatively low number of services, although several small commercial activities are located along Tommaso Natale Road, i.e., the main street of Tommaso Natale neighborhood.

Table 3
Census data (source: ArcGIS Business Analyst database, 2021).

Age group	Number of residents
0–14	3970
15–29	4658
30–44	5295
45–59	6737
Over 60	7129
Total	27,789

As shown in Fig. 3, the main points of interest are in the coastal strip of Mondello and Addaura where there are beaches, hotels, sports centers and restaurants; in Viale dell'Olimpo, where there are several sports centers and a high school; and in Partanna Mondello road where there are several food shops and drugstores. Tommaso Natale train station connects the area with other areas of the city through the railway line.

Indeed, the railway mainly connects the study area with the city centre, with a low frequency (about 1 train per hour). Therefore, this low frequency motivates residents to use their private vehicles for their commuting trips. There are also 7 bus lines, operated by the municipal transportation company AMAT S.p.A. These bus lines also have low frequency; thus, users face high waiting times at stops. It's not surprising that only users who have no other options use the bus, and thus buses always have few passengers on board. Indeed, only 9 % of the residents in the study area use PT (Capodici, D'Angelo, D'Orso, & Migliore, 2022).

To improve the use of PT in the study area, we proposed a microtransit service with flexible routes and on-demand stops located throughout the area and reachable within 10 min by the inhabitants. In the proposed scenario, microtransit will replace the low-frequency bus lines during the off-peak hours, becoming an on-demand mobility option within the study area and a feeder service towards the Palermo Tommaso Natale station. During the peak hours, the microtransit fleet could operate as a conventional PT service with fixed routes and schedules. The fleet consists of nine-seater minivans.

The study area was divided into 136 Traffic Analysis Zones (TAZs), using census tracts' borders as zone limits (Fig. 4). A centroid was assigned to each TAZ and all trips starting or ending in a TAZ were assumed to do so at its centroid.

4.2. Transport supply

The road network was modelled in a GIS software, importing it from OpenStreetMap. Subsequently, we classified the links into roads where microtransit cannot access (private roads or roads where the necessary stopping spaces are not available) and those where the service fleet can transit (Fig. 5).

Therefore, the road network had 4516 links of which 957 can be travelled by the DRT service, constituting the microtransit flexible routes. In addition, the on-demand stops along these routes were defined. All links could be travelled by pedestrians.

We imagined that riders could request a pickup at the existing bus stops. To increase pedestrian access to the service, we added some stops in areas where bus stops didn't exist. A total of 165 virtual stops were defined as PUDO. Centroids were connected to the road and microtransit networks via artificial links known as centroid connectors.

These links were built using a tool in the software QGIS allowing points to be connected to the closest line through virtual links.

4.3. The RP/SP survey

To develop a mode choice model and calibrate it, we conducted a field survey; in this way, we modelled the mode choice behaviour of the

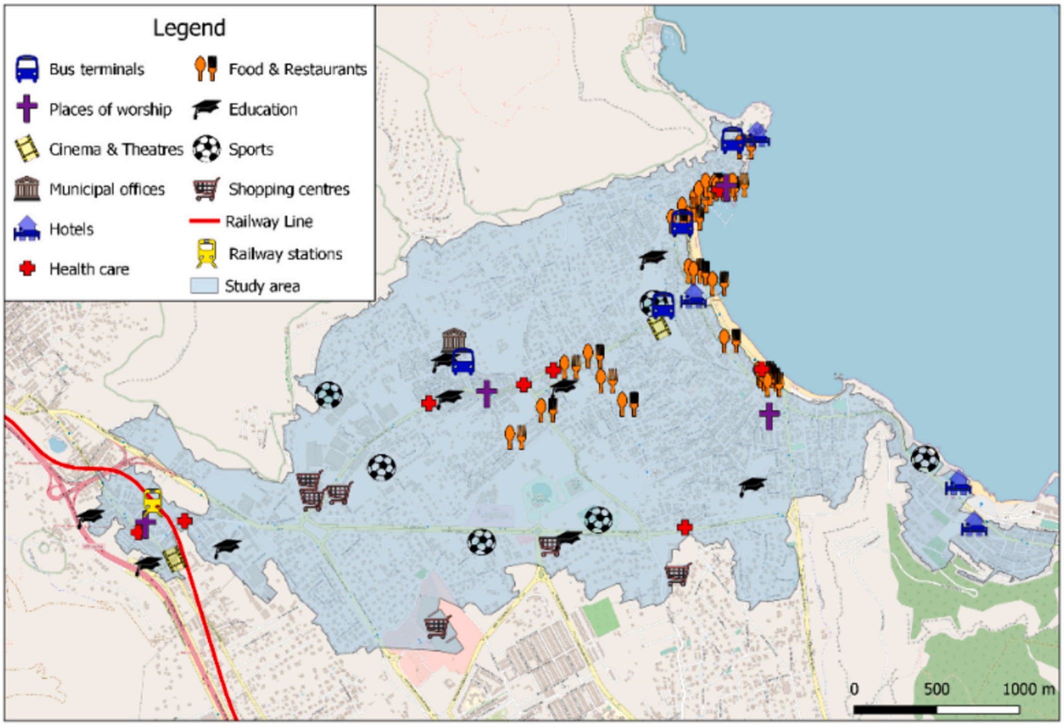

Fig. 3. Study area and points of interest.

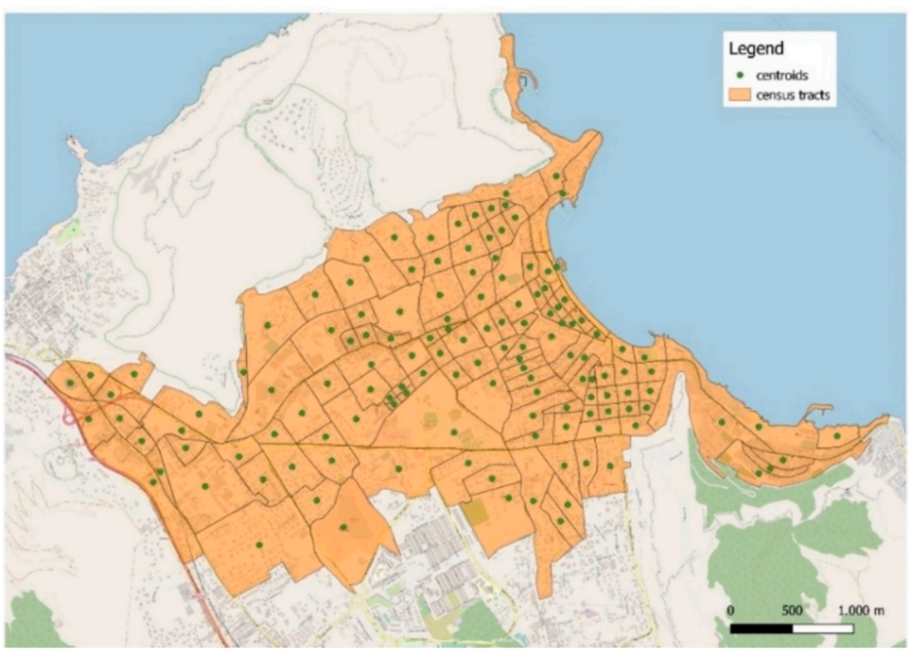

Fig. 4. Traffic Analysis Zones.

residents of the study area and assessed their propensity to use a DRT service. Indeed, we conducted RP and SP surveys simultaneously through the administration of a single questionnaire. An in-depth discussion on the RP/SP survey conducted in the study area and the calibration of the multinomial logit model investigating factors affecting microtransit choice can be found in Capodici, D'Orso, Migliore and Vittorietti, 2024. We reported in this subsection some relevant aspects useful to understand how RP/SP surveys were included in the methodology framework.

The questionnaire consisted of three parts: in the first part, the socio-economic characteristics of the respondents were recorded; in the second part, the mobility habits of the respondents were assessed: the survey administrators asked respondents to recall what trips they made during the day before the survey (recall technique). To reduce the chance that major trips will be forgotten, we asked respondents to think in the framework of activities and places where they did these activities. The last part of the questionnaire was the SP survey, containing a set of choice experiments; four hypothetical scenarios were presented to respondents, asking them to choose between four alternatives (car, motorcycle, walking, and DRT) for each scenario. To preliminary

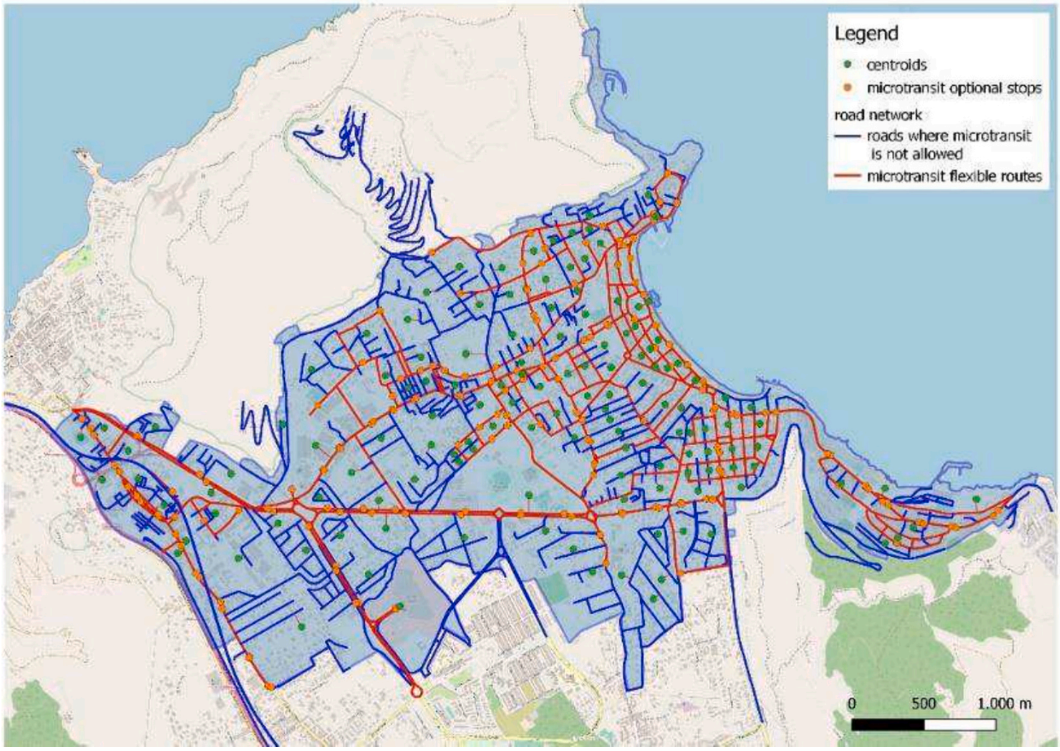

Fig. 5. The road network: roads where microtransit is not allowed (blue lines), microtransit stops (orange points) and flexible routes (red lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

introduce to respondents the discrete choice experiments, a description of the microtransit service was presented to them beforehand. Microtransit was described as a first-mile/last-mile service connecting to a high-capacity or high-regularity transit node (Stazione Palermo Tommaso Natale) and operating during off-peak hours, with PUDO stops within a maximum 10-min walk from the residences and a fare similar to a bus's.

To calculate the desired number of completed surveys, we considered the study budget and timeline. We determined that 145 completed surveys would provide sufficient power to detect significant effects when exploring mode choice preferences and propensity to use microtransit services, i.e. our primary outcomes of interest. A random sampling method was used to form the interview sample, ensuring that it was representative of the population residing in the study area.

We selected and trained some students from the University of Palermo as survey administrators. Personal interviews were conducted during off-peak hours stopping respondents near the main points of interest in the study area. We attempted to reduce response bias by tracking and varying day of week and time of day, although considering working days and off-peak hours. The survey was administered between November 2021 to December 2021 with successful completion of 145 5-min face-to-face interviews.

We used the results of the survey to calibrate a mode choice model, with the help of the statistical software "R". We used a Multinomial Logit model to estimate the choice probability for microtransit for different users' groups (considering age, gender, and level of education as variables). The considered attributes are reported in Table 4. A stepwise regression method with backward elimination was adopted. We started with a model that includes all the variables, then removing one variable and comparing the two models. If the goodness of fit statistics improved, the old model is discarded. Then, a new model is developed while dropping another variable. Many iterations were performed until the model with the most satisfactory results was chosen and presented. Following this approach, we dropped all the variables having not statistical significance, leading to a calibration not affected by non-significant variables. The significant attributes and the results of the model calibration are reported in Table 5.

Travel time, total cost and transfer have negative coefficients: as expected, an increase in the value assumed by these variables means having a decrease in utility. Age is significant for motorcycle, car and microtransit, and having negative signs means that younger people are more willing to use these modes rather than walk (the base alternative). The number of cars per person is significant for car and microtransit, and positive coefficients imply that people having more household cars are more likely to choose the car or microtransit rather than walking. Holding a driving license is significant only for microtransit and the negative coefficient implies that people that don't own a driving license are more inclined to use microtransit. The level of education is significant for all the transport modes and the negative coefficient means that high educated people are more willing to walking rather than use the other transport modes. Moreover, an increase in the level of education implies an increase in the utility associated with microtransit. Based on the results of the calibration and the significant attributes showed in Table 5, the utility function for microtransit was expressed by the following Eq. 3:

$$\begin{aligned} V_{DRT} = {} & \beta_{tmv} \bullet t_{DRT} + \beta_c \bullet C_{tot_{DRT}} + ASC_{DRT} + \beta_{Number\ car_{DRT}} \\ & \bullet Number\ car + \beta_{Driving\ licence_{DRT}} \bullet Driving\ licence + \beta_{Age_{DRT}} \\ & \bullet Age + \beta_{Education_{DRT}} \bullet Education \end{aligned} \tag{3}$$

4.4. The O/D matrix estimation

The next step of the methodology involves estimating the microtransit O/D matrix. Since the proposed microtransit service would operate during off-peak hours, we considered only non-commuting trips, neglecting the contribution that commuters may provide in terms of users. Thus, non-commuting trips generated by each zone were first assessed, developing a trip generation model. They were calculated as a function of the number of people living in each zone divided into two

Table 4
Attributes of the mode choice model.

Attribute	Symbol	Description
Walking time	$t_{walking}$	Travel time for walking as transport mode.
Motorized travel time	$t_{motorized}$	Time that motorized vehicles (motorbike, car and microtransit) spend to complete the trip. Motorbike: in-vehicle time; car: in-vehicle time and parking time; microtransit: in-vehicle time, waiting time and walking time to the nearest microtransit stop.
Total travel cost	C_{tot}	Motorbike: fuel cost; Car: fuel cost and parking rate; microtransit: cost of the ticket plus the cost of the conventional PT service ticket, if any.
Transfer	*Transfer*	Binary variable. 0: no transfers towards other conventional PT systems; 1: otherwise.
Alternative Specific Constant	$ASC_{motorbike}$ ASC_{car}, ASC_{DRT}	Alternative specific constants for motorbike, car and microtransit respectively.
Age	$Age_{motorbike}$, Age_{car}, Age_{DRT}	Middle value of the age groups considered in the questionnaire (22 for age between 15 and 29; 37 for age between 30 and 44; 52 for age between 45 and 59; 67 if the age is between 60 and 74; 82 if the respondent is older than 74).
Gender	$Gender_{motorbike}$, $Gender_{car}$, $Gender_{DRT}$	Binary variable relating to the gender of the respondents (0 for males and 1 for females).
Number of cars per person	$Numbercar_{motorbike}$, $Numbercar_{car}$, $Numbercar_{DRT}$	Number of cars owned per person per household. This variable is obtained from the ratio of the number of cars owned per household to the number of members in the household, as recorded in the RP survey.
Driving license	$Drivinglicence_{motorbike}$, $Drivinglicence_{car}$, $Drivinglicence_{DRT}$	Binary variable which is equal to 1 in case of driving license ownership and 0 otherwise.
Education	$Education_{motorbike}$, $Education_{car}$, $Education_{DRT}$	Number of years needed to obtain a specific qualification (5 for primary school certificate, 8 for junior high school diploma, 13 for high school diploma and 17 for degree).

age groups: a first group of users with residents aged between 15 and 59 and a second group with residents aged over 60. For these two user groups, trip generation rates for non-commuting trips were estimated as the average between the rates detected by the Audimob Observatory (ISFORT, 2021) and those detected by the RP survey. This approach was followed because the sample is small (1 %) and only people who made trips were interviewed, so using trip generation rates derived from the RP survey could lead to an overestimation of the real generation rates.

By multiplying the number of residents in a zone belonging to an age group by the relative trip generation rate, the total number of non-commuting trips originated by that zone was calculated.

A gravity model was then applied as trip distribution model. Non-commuting trips attracted by each zone were estimated according to the attractiveness of the zone in terms of the percentage of employees in retail and service sector working in that zone compared to the number of employees working in the study area. The distance between centroids was considered as a cost. Indeed, the number of non-commuting trips generated by zone *o* and attracted by zone *d* was estimated using the following Eq. 4:

$$n_{od} = n_o \frac{{A_d}^{b_1} e^{-b_2 * x_{od}}}{\sum_{\forall j} {A_j}^{b_1} e^{-b_2 * x_{oj}}} \tag{4}$$

where n_o is the number of non-commuting trips generated by zone *o*, A_d is the number of employees in retail and service sector working in the zone *d*; x_{od} is the distance between zone *o* and zone *d*; $b_1 = 0.4$ and $b_2 = 0.05$ are coefficients calibrated for non-commuting trips made in the city of Palermo during the drafting of the Urban Traffic Plan. Non-commuting trips attracted by external centroids are also estimated as a function of the attractiveness of areas outside the study area, expressed in terms of the number of trips made by respondents stated in the RP survey. External-internal trips were not considered.

Non-commuting trips made by microtransit derive from the application of the mode choice model. Indeed, trips made by microtransit are a fraction of total non-commuting trips. Therefore, the OD matrix for non-commuting trips made by microtransit by users belonging to the socio-economic category *i* has as element m^i_{od} the product between the number of total non-commuting trips between zone *o* and zone *d* and the choice probability for microtransit for this *od* pair considering the socio-economic category *i*. Considering the same socio-economic category, the choice probability for DRT varies for each OD pair since the travel times for the various modes of transport are different from one OD pair to the others. In the first case, we considered a fare for microtransit equal to € 1.5.

The OD matrix for non-commuting trips made by microtransit is the sum of all the matrices for non-commuting trips made by microtransit for each socio-economic category. Then, we hypothesized a temporal distribution of the non-commuting trips made by microtransit to define the OD matrix for non-commuting trips made by microtransit during the morning.

To consider how the fare affects the use of the service, we considered different service fares (i.e. four levels: € 1.50, € 2.00, € 2.50, € 3.00), determining different choice probabilities for microtransit. Thus, repeating the method for the other price levels, we identified four different OD matrices considering a different willingness to pay of users for the DRT service. Starting from a rate of 1.50 € and considering incremental steps of 50 cents, four different O/D matrices were obtained, respectively:

- Matrix for scenario 1: considering a fare of € 1.50 resulted in 1919 trip requests;
- Matrix for scenario 2: considering a fare of € 2.00 resulted in 1785 trip requests;
- Matrix for scenario 3: considering a fare of € 2.50 resulted in 1659 trip requests;
- Matrix for scenario 4: considering a fare of € 3.00 resulted in 1537 trip requests.

4.5. The simulation model

Each O/D matrix was used as demand input in the simulation model implemented through the VISUM software. In the disaggregation procedure, the demand was equally assigned from the zones to the nodes. Specifically, the demand was distributed over 1012 of the 1800 nodes within the study area. Simulations were carried out for all four scenarios, assigning the demand on the DRT network. These simulations, in addition to providing the output parameters defined in the methodology section, allowed us to observe the flows on the network deriving from the assignments of the four OD matrices. In detail, both the DRT volumes on board (DRT_vol) and the pedestrian flows to arrive at the stops or to the destination node (Volume Tsys [Pers]) were analyzed. Fig. 6 shows the results relating to the assignment of the OD matrix for scenario 1.

As for the other simulation input parameters, they were considered constant for the four simulated scenarios.

Table 5
Significative attributes (Significance: 0 (***); 0.001 (**); 0.01 (*); 0.05 (.); 0.1 (,)) (from Capodici, D'Orso, Migliore and Vittorietti, 2024).

	Coeff β	Std. Err.	z	P > |z|	
$t_{walking}$	−0.0886945	0.0148455	−5.97	0.000	***
$t_{\text{motorized vehicles}}$	−0.0120287	0.0070721	−1.70	0.089	,
C_{tot}	−0.1987762	0.0448350	−4.43	0.000	***
Transfer	−0.7227308	0.2664712	−2.71	0.007	**
$ASA_{\text{motorcycle}}$	9.7808605	2.6472395	3.69	0.000	***
ASA_{car}	8.0833144	2.5087600	3.22	0.001	**
ASA_{DRT}	10.7439860	2.5182978	4.27	0.000	***
Motorcycle					
Age	−0.1790616	0.0321480	−5.57	0.000	***
Gender	−2.4914474	0.7297172	−3.41	0.001	***
Level of education	−0.3999587	0.1131814	−3.53	0.000	***
Car					
Age	−0.1262652	0.0302785	−4.17	0.000	***
Cars per person	4.7736104	1.2125511	3.94	0.000	***
Level of education	−0.3357910	0.0977002	−3.44	0.001	***
DRT					
Age	−0.1320482	0.0301695	−4.38	0.000	***
Cars per person	3.3907248	1.2030916	2.82	0.005	**
Driving license possession	−1.5824563	0.7650447	−2.07	0.039	*
Level of education	−0.3049811	0.0962529	−3.17	0.002	**

Log-Likelihood: −469.31; Likelihood ratio test: chisq = 233.52 (p.value ≤ 2.22e-16); McFadden R^2: 0.19923.

Fig. 6. The assignment of the OD matrix for scenario 1: pedestrian flows (green) and DRT volumes on board (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5. Results and discussion

To simulate the possible operational configurations of the microtransit service, due to the demand variation, several simulations were performed. Specifically, we assumed a fixed OD matrix for each scenario, and we performed ten runs of simulation for each of them. Thus, for each run, the procedure for the generation of trip requests disaggregated the O/D demand from origin and destination zones by stochastically associating each trip request to nodes contained within these zones. So, we were able to simulate the demand variation associating a request with a different origin node, destination node and desired departure time, varying for each run of simulation. In this way, the generated list of trip requests was characterized by variations in terms of their spatial and temporal distribution.

Therefore, for each scenario we performed ten simulations, obtaining ten lists of trip requests served through the dispatcher procedure, by generating ten different service operational configurations.

We summarize in Table 6 the statistics associated for each scenario, obtained from the simulations. For the considered KPIs, we report the average value μ, the standard deviation σ and the coefficient of variation CV.

Considering around 9000 non-commuting trips made by people living in the study area during the morning (Capodici, D'Orso, Migliore and Vittorietti, 2024), we found that non-commuting trips which could be made using microtransit goes from around 20 % in the Scenario 1 to around 16 % in the Scenario 4.

The average Detour Factor experienced by users goes from 2.75 for Scenario 4 to respectively 2.76 and 2.77 for Scenarios 2 and 3. This

Table 6
Summary statistics of output simulation runs for the considered scenarios.

Output parameters	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
	μ	σ	CV	μ	σ	CV	μ	σ	CV	μ	σ	CV
Pass DRT [pass]	1882	4.34	0.23 %	1748	6.65	0.38 %	1625	5.36	0.33 %	1507	7.43	0.49 %
Experienced DF	2.75	0.02	0.66 %	2.76	0.02	0.80 %	2.77	0.03	0.94 %	2.75	0.02	0.83 %
T wait [min, *sec*]	5.42	0.03	0.49 %	5.41	0.05	0.97 %	5.37	0.06	1.12 %	5.33	0.10	1.85 %
T O/PUDO [min, sec]	5.11	0.05	0.90 %	5.12	0.04	0.84 %	5.11	0.05	1.00 %	5.13	0.10	2.02 %
T PUDO/D [min, sec]	3.45	0.06	1.87 %	3.46	0.03	0.98 %	3.46	0.04	1.21 %	3.47	0.06	1.64 %
In-vehicle DT [min, sec]	10.21	0.06	0.57 %	10.19	0.10	0.97 %	10.28	0.09	0.92 %	10.20	0.11	1.11 %
Vehicles [vehicles]	32	1.08	3.32 %	30	1.57	5.17 %	29	1.78	6.24 %	27	1.56	5.79 %
V DRT [km]	21.95	0.08	0.36 %	21.97	0.09	0.39 %	21.98	0.07	0.34 %	22.00	0.09	0.41 %
Km all [km]	2521	47.18	1.87 %	2352	39.10	1.66 %	2226	49.38	2.22 %	2075	35.25	1.70 %
Pass all [pass]	58	1.91	3.29 %	57	3.12	5.40 %	57	3.35	5.86 %	56	3.49	6.21 %

means that users will experience a travel time around 2.7 times higher than the one needed for traveling using a direct route without detours. The walking time to reach the pick-up points is around 5 min for all the Scenarios, while the walking time to reach the destination from the drop-off points does not exceed 4 min. The waiting time at stops is around 5 min, while the in-vehicle Detour time is around 10 min. These values are consistent with the values used as input parameters in the mode choice model.

The fleet needed to satisfy the travel requests is composed of a minimum of 27 vans for Scenario 4 and a maximum of 32 vans for Scenario 1.

Comparative analyses of the four scenarios were carried out in order to identify the impact of changes in the fleet on the performance of the DRT service.

As can be seen in Table 6, low variations in KPIs were registered. These variations are due to the different service operational configurations required to satisfy demand, which demonstrates the adaptability of the service to demand variations while guarantying the required quality standards (e.g. maximum waiting time; walking time and in-vehicle time). Therefore, the following evaluations are provided considering the average values for the KPIs of each scenario.

Fig. 7 shows the trend in the percentage of passengers served by DRT for the four scenarios. It can be observed that not all the travel requests are satisfied by the service. However, the number of users served by the service is always higher than 97.9 % of the total users that make a travel request.

This occurs because OD pairs associated with trips of less than 1.8 km were excluded during the demand reconstruction procedure, because it was more comfortable to make the journey walking. Furthermore, in the disaggregation of the demand, from a zonal OD matrix to a nodal OD matrix, the "isolated" nodes of the network were excluded, in correspondence with which a generation of travel demand was not assumed.

Analyzing the operational parameters associated with the service, it is evident that an increase in the number of vehicles to perform the service does not lead to an increase in the percentage of served passengers. Moreover, load factor of the vehicles is around an average value of 56 % (see Fig. 8).

Reducing the number of vehicles available to perform the service, this does not lead to an increase in the load factor, but rather to a decrease in the number of served users. This is due to the distribution of demand over a large area and the generation of individual travel requests.

Fig. 9 shows that reducing the percentage of satisfied requests from 98 % to 95 % leads to a reduction in the number of vehicles from a minimum of 7 % in the scenario 2 and scenario 3 up to a maximum of 11 % in the scenario 4 (9 % in the scenario 1). This is an important result in the view of optimizing the service: in fact, while maintaining the percentage of satisfied requests very high (i.e. 95 %), a significant reduction in the number of vehicles is obtained, thus with an advantage for the service providers.

By analyzing the parameters associated with the user experience, Fig. 10 compares the results obtained for the four scenarios in terms of travel times. Considering the sum of the walking time to reach the stop from the origin node, the increase in in-vehicle time due to the detours and the walking time to reach the destination from the drop-off point, this value remains almost constant in the four analyzed scenarios. This means that the DRT service maintains constant performance with changes in the demand and number of vehicles.

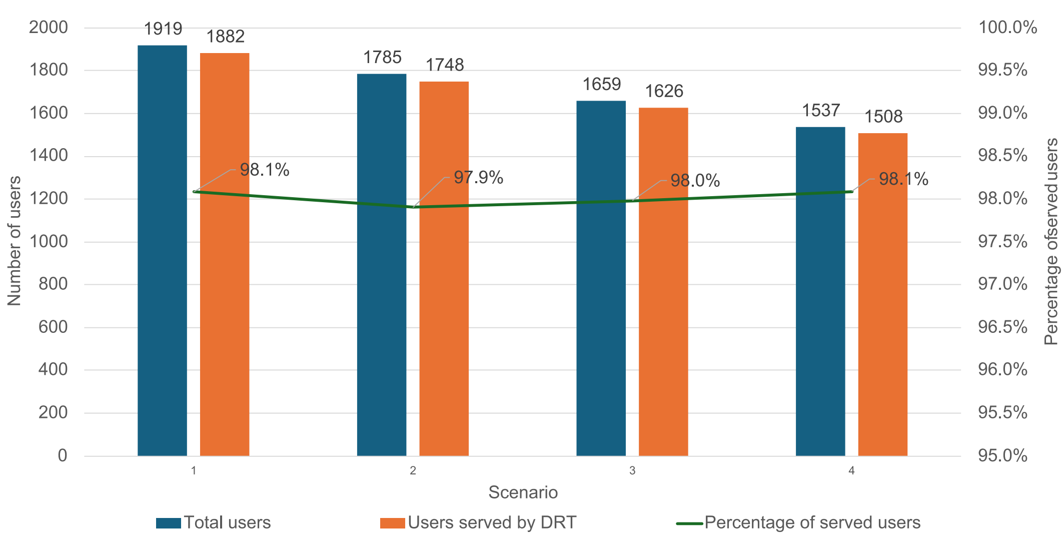

Fig. 7. Comparative analysis of the total number of users (trip requests) and percentage of passengers served with the DRT.

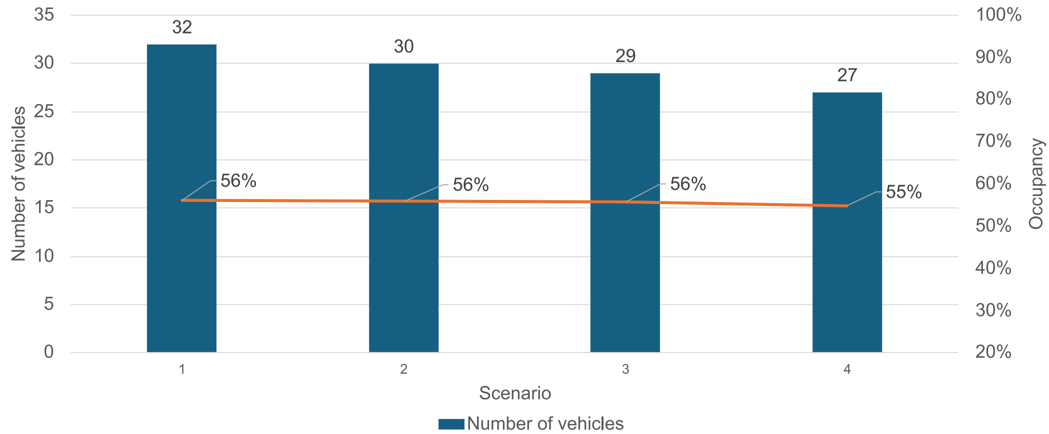

Fig. 8. Comparative analysis of the relationship between the number of vehicles and load factors.

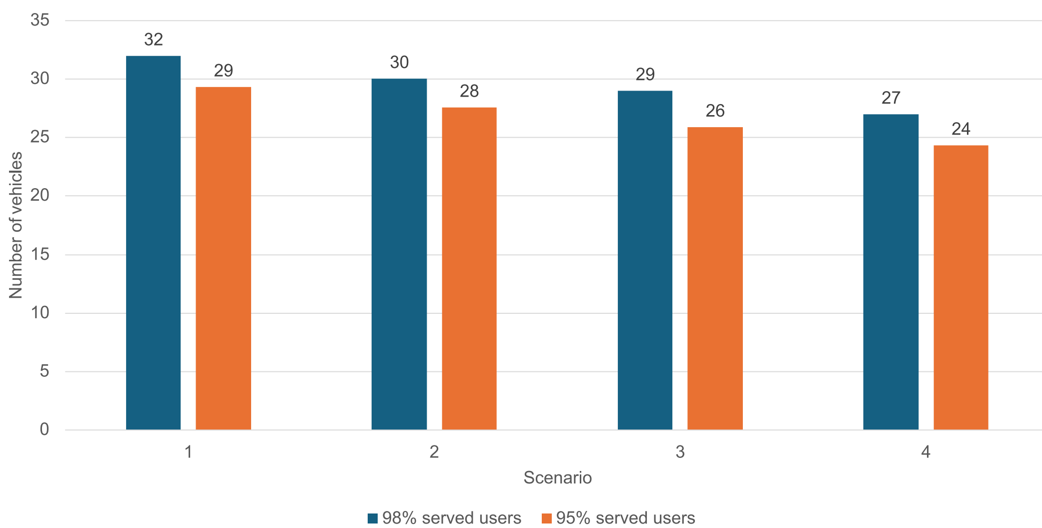

Fig. 9. Number of vehicles for the DRT service and its optimization.

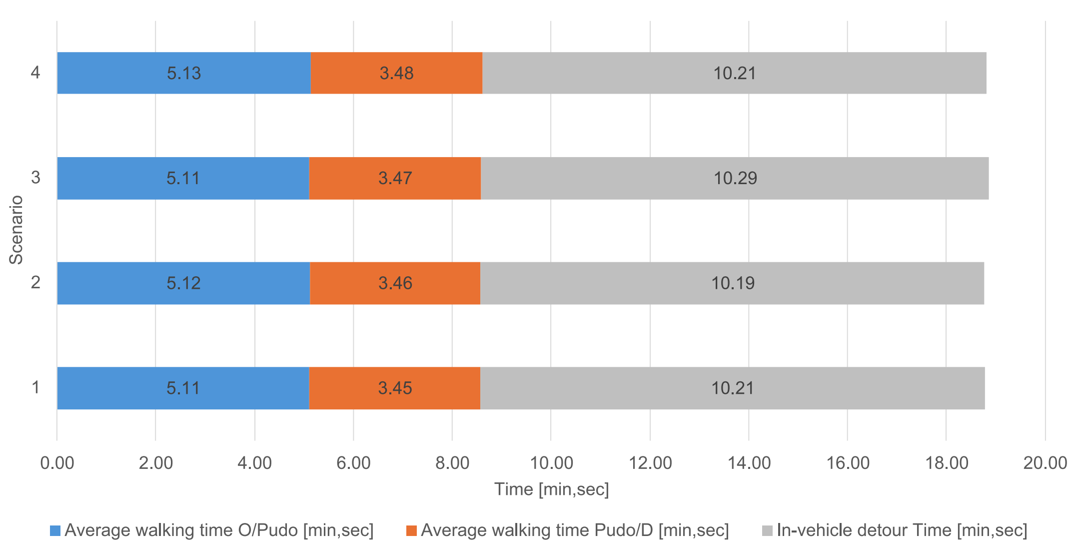

Fig. 10. Comparative analysis of travel times.

In the final step, we assessed the change in users' satisfaction, the revenues, the operating costs and the externalities for the four scenarios (Table 7). The revenues increase with increasing fare, because despite the fare increases, served demand slightly decreases (from 1882 to 1507 users), but pays more. Operating costs decrease with increasing fare because fewer vehicles are needed (from 32 to 27) and fewer kilometers

Table 7
Sensitivity analysis: consumer surplus, revenues, operating costs, externalities, and objective function.

Variables	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Consumer surplus [€]	2600.46	730.15	−1008.5	−2621.9
Revenues [€]	5915	7079	8042.4	8799.4
Operating costs [€]	5625.8	4821.6	4344.8	3573
Externalities [€]	161.26	135.37	105.6	82.06
Objective function (as calculated with Eq. 2)	3050.92	3122.92	2794.74	2686.61

are travelled by the service vehicles. The users' satisfaction decreases as microtransit fare increases, because an increase in the fare does not correspond to an improvement in service performance, which remains almost costant across the scenarios, and thus making the users less satisfied. Externalities increase with the increasing fare because users and kilometers travelled by them using PT decrease, while the kilometers travelled by private cars increase. As it can be noted, operating costs decrease less than user satisfaction because, even if there is a reduction in users with increasing fare, a given number of vehicles is always needed to maintain good service performance. Indeed, considering scenarios 2 and 3, demand decreases but the number of vehicles needed remains almost constant (going from 30 to 29).

The objective function has the maximum value when the microtransit fare is € 2.00 (Scenario 2). Considering that microtransit could replace up to 8 buses during off-peak hours, the service with a fare of € 2.00 would be financially sustainable as it could take advantage of the municipal and regional funding that the PT company currently receives for the operation of these 8 buses. Finally, Scenario 2 is the best scenario: the microtransit service with 30 nine-seater vans and costing € 2.00 serves a high number of users and has good performances, while guaranteeing the financial sustainability.

6. Concluding remarks

This paper presented an integrated methodological approach to design a microtransit service in a suburban area. The transport demand was assessed through the simultaneous administration of RP and SP surveys, which allows for developing a mode choice model and estimating the propensity to use microtransit by people living in a suburban area. Then, it was demonstrated how GIS software could be a valuable tool to model the supply, building the road network and the microtransit network with flexible routes and on-demand stops, and how simulation models are powerful tools for optimizing the fleet and setting the fares for on-demand services. As far as we know, this is one of the few studies using an integrated approach to model microtransit demand and design different features of a microtransit service (e.g. routes, PUDOs, fleet size, and fares), verifying the economic financial sustainability of the service. Moreover, few studies used the SP survey to predict microtransit choice and this paper is the only one that made it considering the Italian context.

A suburban area in Palermo (Italy) was chosen as study area since this part of the city is not well connected with the city centre and the PT services have poor regularity and low frequency. Indeed, a survey conducted in the study area found that people may experience a waiting time that can reach up to 20 min.

The results highlight how introducing a microtransit service could change the mobility habits of people living in suburban areas. Indeed, from the user perspective, the service is flexible and improves accessibility, constituting an effective transport alternative to the private vehicles and a reliable option to reach social services, education, and job opportunities in a faster and easier way. The increase in accessibility is mainly due to the introduction of stops in areas not covered by the existing bus stops;

Moreover, the access to essential services is higher with microtransit rather than the existing bus service because, spatially, there are more PUDOs than the existing bus stops and, temporally, people can make trips avoiding the fixed schedules of conventional PT services. As the simulation showed, PUDOs are within 10 min walking from origins and destinations, and the average walking time spent by users is around 8 min. Indeed, the travel experience of people living in suburban areas and usually using PT could be improved by the introduction of the microtransit service; moreover, there is a reduction in waiting times and a greater number of POIs reachable in less time. The waiting times at stops are around 5 min for all scenarios: these waiting times are significantly lower than those currently experienced by PT users. These time-related results are more or less similar among the four scenarios, even if a rationalisation of the vehicle fleet is carried out. These improvements would cause PT use to increase from the current 9 % to around 20 %, as shown in Capodici, D'Orso, Migliore and Vittorietti, 2024.

The travelled kilometers decrease proportionally to the reduction of the OD matrix considered in each of the four scenarios; whereas, the number of vehicles does not decrease proportionally (i.e. if demand decreases by 20 %, it should decrease by about 6 vehicles between one scenario and the next one). However, this does not happen because in order to guarantee good performance and satisfy trip requests, the service must have a well-sized fleet.

From the service provider perspective, the advantage is represented by the ability to implement a service which is able to meet the demand reduction in off-peak hours, optimizing the service and maintaining high performances. This consideration is significant if we make a comparison with conventional PT services: indeed, for conventional bus services, a reduction in the number of vehicles due to a decreasing demand usually results in a reduction in service hours and shorter routes with a consequent increase of the average waiting time, thus considerably reducing the performance of the service. A microtransit service operating as on-demand service during off-peak hours and as a fixed route service during peak hours may maintain high performances and alleviate access inequality, especially for vulnerable rider groups.

6.1. Limitations and further works

This research has some limitations. The first limitation is that we consider spatially and timing demand variation but not considering the day-to-day equilibrium. This means that no day-to-day adjustment processes were developed. Realistically, passengers learn and adjust their choices day-to-day, as well as the operator is likely to have a day-to-day dynamic operating policy, updating its policy as a result of learning from the users (modifying the service coverage, the fleet size or the fares). In particular, variations in transport demand between weekdays and weekends were not considered, by referring only to average working day demand. Therefore, the demand may be overestimated, and the fleet size needs to be adjusted to fit the demand variation. To overcome this limitation, an agent-based model could be developed taking into account the day-to-day adjustment process described by Djavadian and Chow (2017).

A second limitation is not considering commuting trips in the estimation of the microtransit demand. Surely, the possibility of having extra time due to detours is a feature leading microtransit to better serve non-commuting trips without time constraints rather than commuting trips with time constraints. However, microtransit services may be used for both commuting and non-commuting trips; thus, an increase in the estimated microtransit demand could be derived from users undertaking commuting trips. However, in our case study, the on-demand service would operate during off-peak hours; thus, the contribution of commuting trips in the estimation of the microtransit demand is not expected to be high. Further studies, which take a variation in fare based on different groups of users (students, the elderly, etc.) into account, will need to be performed. Moreover, we will test the methodology considering other types of microtransit.

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CRediT authorship contribution statement

Alessandro Emilio Capodici: Software, Methodology, Data curation. **Martina Citrano:** Writing – original draft. **Gabriele D'Orso:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Conceptualization. **Marco Migliore:** Supervision, Methodology, Funding acquisition. **Matteo Ignaccolo:** Supervision, Funding acquisition. **Pierfrancesco Leonardi:** Writing – original draft, Visualization, Software. **Vincenza Torrisi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, 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.

Data availability

Data will be made available on request.

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